Technical Support Document

Corporate Average Fuel Economy Standards for Passenger Cars and Light Trucks for Model Years 2027 and Beyond and Fuel Efficiency Standards for Heavy-Duty Pickup Trucks and Vans for Model Years 2030 and Beyond

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U.S. Department of Transportation
National Highway Traffic Safety Administration

NHTSA

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Table of Acronyms and Abbreviations

Abbreviation	Term
AAA	American Automobile Association
AALA	American Automotive Labeling Act
ABS	Antilock Braking Systems
AC	Air Conditioning
ACAS	Automotive Collision Avoidance System
ACC	Advanced Clean Cars (including versions ACC I and ACC II)
ACT	Advanced Clean Trucks
ADAS	Advanced Driver Assistance Systems
ADEAC	Advanced Cylinder Deactivation
ADEACD	Advanced Cylinder Deactivation with Dual Overhead Camshaft
ADEACS	Advanced Cylinder Deactivation with Single Overhead Camshaft
ADSL	Advanced Diesel Engine
ADVENG	non-basic engine technologies
AEB	Automatic Emergency Braking
AEO	Annual Energy Outlook
AER	All-Electric Range
AERO	aerodynamic drag technology
AERO0	baseline level of aerodynamic improvement
AFV	Alternative Fuel Vehicle
AGM	Absorbed-Glass-Mat
AHSS	Advanced High Strength Steel
AIC	Akaike Information Criterion
AIS	Abbreviated Injury Scale
AKI	Anti-Knock Index
AL	Aluminum
AMPC	Advanced Manufacturing Production Tax Credit
AMTL	Advanced Mobility Technology Laboratory
ANL	Argonne National Laboratory
APA	Administrative Procedure Act
AT	Automatic Transmissions
AT	traditional automatic transmissions
AWD	All-Wheel Drive
BAC	Blood Alcohol Concentration
BAS	Brake Assistance Systems
BCG	Boston Consulting Group
BEA	Bureau of Economic Analysis

Abbreviation	Term
BEV	Battery Electric Vehicle
BISG	Belt Integrated Starter Generator
BLIS	Blind Spot Information System
BLS	Bureau of Labor Statistics
BMEP	Brake Mean Effective Pressure
BMW	BMW of North America, LLC
BNEF	Bloomberg New Energy Finance
BPT	Benefit-Per-Ton
BSA	Blind Spot Alert
BSD	Blind Spot Detection
BSFC	Brake-Specific Fuel Consumption
BTU	British Thermal Unit
BTW	Brake and Tire Wear
CAA	Clean Air Act
CAFE	Corporate Average Fuel Economy
CARB	California Air Resources Board
CARS	Car Allowance Rebate System
CBI	Confidential Business Information
CD	Charge-Depleting
CDS	Crashworthiness Data System
CEGR	Cooled Exhaust Gas Recirculation
CFR	Code of Federal Regulations
CFRP	Carbon Fiber Reinforced Plastic
CH_4	Methane
CI	Compression Ignition
CIB	Crash Imminent Braking
CIR	Combined Injury Risk
CISG	Crank Integrated Starter Generator
CL	Cost Learning
CMB	Gross Combined
CNG	Compressed Natural Gas
CO	Carbon Monoxide
CO_2	Carbon Dioxide
CONFIG	engine cam configuration
CONV	Conventional Powertrain
COV	Coefficient of Variation
COVID-19	Coronavirus disease of 2019
CPI	Consumer Price Index

Abbreviation	Term
CPM	Cost Per Mile
CR	Compression Ratio
CRSS	Crash Report Sampling System
CUV	Crossover Utility Vehicle
CVC	Clean Vehicle Credit
CVT	Continuously Variable Transmission
CVTL	Continuously Variable Transmission with Level
CY	Calendar Year
CZMA	Coastal Zone Management Act
DBS	Dynamic Brake Support
DC	Direct Current
DCT	Dual Clutch Transmission
DD	Direct Drive Transmission
DEAC	Dynamic Cylinder Deactivation
DFS	Dynamic Fleet Share
DLR	Dynamic Road Load
DMC	Direct Manufacturing Costs
DOE	U.S. Department of Energy
DOHC	Dual Overhead Camshaft
DOI	Department of the Interior
DOT	U.S. Department of Transportation
DSLI	advanced diesel engine with improvements
DSLIAD	advanced diesel engine with improvements and advanced cylinder deactivation
E.O.	Executive Order
EC	Elemental Carbon
ECU	Engine Control Unit
EERE	Office of Energy Efficiency and Renewable Energy
EETT	Electrical and Electronics Technical Team
EF	Emission Factor
EFR	Engine Fiction Reduction
EGR	Exhaust Gas Recirculation
EIA	U.S. Energy Information Administration
EIS	Environmental Impact Statement
EISA	Energy Independence and Security Act of 2007
ELEC	electrification
EM	Electric Motor
EPA	U.S. Environmental Protection Agency
EPCA	Energy Policy and Conservation Act of 1975

Abbreviation	Term
EPS	Electric Power Steering
EREV	Extended Range Electric Vehicle
ESC	Electronic Stability Control
ETDS	Electric Traction Drive System
ETW	Equivalent Test Weight
EU	European Union
EV	Electric Vehicle
FARS	Fatal Accident Reporting System
FCA	Fiat Chrysler Automobiles
FCEV	Fuel Cell Electric Vehicle
FCIV	Fuel Consumption Improvement Value
FCV	Fuel Cell Vehicle
FCW	Forward Collision Warning
FE	Fuel Efficiency
FFV	Flexible Fuel Vehicle
FHWA	Federal Highway Administration
FMVSS	Federal Motor Vehicle Safety Standards
FP	Fuel Price
FR	Fatality Rate
FRIA	Final Regulatory Impact Analysis
FTP	Federal Test Procedure
GCVW	Gross Combined Weight
GCWR	Gross Combined Weight Rating
GDP	Gross Domestic Product
GES	General Estimates System
GHG	Greenhouse Gas
GM	General Motors
GMC	General Motor Company
gpm	gallons per mile
GREET	Greenhouse gases, Regulated Emissions, and Energy use in Transportation
GVW	Gross Vehicle Weight
GVWR	Gross Vehicle Weight Rating
GWh	Gigawatt hours
GWU	George Washington University
HCR	High Compression Ratio
HCRD	Atkinson enabled engine with DEAC
HCRE	Atkinson enabled engine
HD	Heavy-Duty

Abbreviation	Term
HDPUV	Heavy-Duty Pickups and Vans
HEG	High Efficiency Gearbox
HEV	Hybrid Electric Vehicle
HFET	Highway Fuel Economy Test
HP	Horsepower
HSS	High Strength Steels
HTF	Highway Trust Fund
HVAC	Heating, Ventilation, and Air Conditioning
HWFET	Highway Fuel Economy Test
IACC	improved accessories
IACMI	Institute for Advanced Composites Manufacturing Innovation
IAV	Ingenieurgesellschaft Auto und Verkehr's engine models
IC	Internal Combustion
ICCT	International Council on Clean Transportation
ICE	Internal Combustion Engine
ICM	Indirect Cost Multiplier
iEGR	Internal Exhaust Gas Recirculation
IFR	Interim Final Rule
IIHS	Insurance Institute for Highway Safety
IMEP	Indicated Mean Effective Pressure
IPC	Imported Passenger Car
IRA	Inflation Reduction Act
IWG	Interagency Working Group
JLR	Jaguar Land Rover
KABCO	scale used to represent injury severity in crash reporting
LBNL	Lawrence Berkeley National Laboratory
LCA	Lane Change Alert
LD	Light-Duty
LDB	Low Drag Brakes
LDV	Light-Duty Vehicle
LDW	Lane Departure Warning
LEV	Low-Emission Vehicle
LFP	Lithium Iron Phosphate
LIB	Lithium-Ion Batteries
LIDAR	Light Detection and Ranging
LIVC	Late Intake Valve Closing
LKA	Lane Keep Assist
LT	Light Trucks

Abbreviation	Term
LTV	Light Trucks and Vans
MAIS	Maximum Abbreviated Injury Scale
MAX	maximum values
MCT	Multi-Cycle Test
MD	Medium-Duty
MDHD	Medium-Duty and Heavy-Duty
MDPC	Minimum Domestic Passenger Car
MDPCS	Minimum Domestic Passenger Car Standard
MDPV	Medium-Duty Passenger Vehicle
MIN	minimum values
MIT	Massachusetts Institute of Technology
MOU	Memorandum of Understanding
MOVES	Motor Vehicle Emission Simulator (including versions MOVES3 and MOVES4)
MPG	Miles Per Gallon
mph	Miles Per Hour
MR	Mass Reduction
MSRP	Manufacturer Suggested Retail Price
MY	Model Year
NA	Naturally Aspirated
NAAQS	National Ambient Air Quality Standards
NADA	National Automotive Dealers Association
NAICS	North American Industry Classification System
NAS	National Academy of Sciences
NASEM	National Academies of Sciences, Engineering, and Medicine
NASS	National Automotive Sampling System
NBER	National Bureau of Economic Research
NCA	Nickel Cobalt Aluminum
NCAP	New Car Assessment Program
NCSA	National Center for Statistics and Analysis
NEMS	National Energy Modeling System
NEPA	National Environmental Policy Act
NESCCAF	Northeast States Center for a Clean Air Future
NHTS	National Household Transportation Survey
NHTSA	National Highway Traffic Safety Administration
NMC	Nickel Manganese Cobalt
NO_X	Nitrogen Oxide
NPRM	Notice of Proposed Rulemaking
NRC	National Research Council

Abbreviation	Term
NREL	National Renewable Energy Laboratory
NRVMT	VMT excluding rebound miles
NTTAA	National Technology Transfer and Advancement Act
NVH	Noise-Vibration-Harshness
NVPP	National Vehicle Population Profile
NZEV	Near Zero-Emissions Vehicles
OC	Off-Cycle
OEM	Original Equipment Manufacturer
OHV	Overhead Valve
OMB	Office of Management and Budget
OPEC	Organization of the Petroleum Exporting Countries
ORNL	Oak Ridge National Laboratory
PADD	Petroleum Administration for Defense District
PAEB	Pedestrian Automatic Emergency Braking
PC	Passenger Car
PDO	Property Damage-Only
PEF	Petroleum Equivalency Factor
PFI	Port Fuel Injection
PHEV	Plug-in Hybrid Electric Vehicle
PIC	NHTSA's CAFE Public Information Center
PM	Particulate Matter
$PM_{2.5}$	Particulate matter 2.5 microns or less in diameter
PMY	Pre-Model Year
PRIA	Preliminary Regulatory Impact Analysis
PS	Power Split
PV	Passenger Vehicle
RADAR	Radio Detection and Ranging
RCD	Reverse Collision Detection
RDPI	Real Disposable Personal Income
RIA	Regulatory Impact Analysis
ROLL	tire rolling resistance
RPE	Retail Price Equivalent
RPM	Revolutions Per Minute
RRC	Rolling Resistance Coefficient
RWD	Rear-Wheel Drive
SAE	Society of Automotive Engineers
SAFE	Safer Affordable Fuel-Efficient
SAX	Secondary Axle Disconnect

Abbreviation	Term
SBREFA	Small Business Regulatory Enforcement Fairness Act
SC	Social Cost
SC-CO2	Social Cost of Carbon Dioxide
scf	standard cubic feet
SC-GHG	Social Cost of Greenhouse Gases
SCO	Synthetic Crude Oil
SGDI	Stoichiometric Gasoline Direct Injection
SGDID	Dual Over-Head Cam Engine and Gasoline Direct Injection
SGDIS	Single Over-Head Cam Engine and Gasoline Direct Injection
SHEV	Strong Hybrid Electric Vehicle
SHEVP	Power Split Strong Hybrid Electric Vehicle
SI	Spark Ignition
SIR	Societal Injury Risk
SKIP	refers to skip input in market data input file
SO_2	Sulfur Dioxide
SOC	State of Charge
SOHC	Single Overhead Camshaft
SO_X	Sulfur Oxide
SPR	U.S. Strategic Petroleum Reserve
SS12V	Stop-Start 12V Hybrid Electric Vehicle
S-SBR	Solution Styrene Butadiene Rubber
SUV	Sport Utility Vehicle
SwRI	Southwest Research Institute
TAR	Technical Assessment Report
TC	Turbocharged Aspiration
TCU	Transmission Control Unit
TPMS	Tire Pressure Monitoring System
TS&D	Fuel Transportation, Storage, and Distribution
TSD	Technical Support Document
TTW	Tank-to-Wheel
TURBO0	reference baseline turbocharged downsized technology
TURBO1	turbocharged downsized technology
TURBO2	advanced turbocharged downsized technology
TURBOAD	turbocharged engine with advanced cylinder deactivation
TURBOD	turbocharged engine with cylinder deactivation
TURBOE	turbocharged engine with cooled exhausted recirculation
TWh	Terawatt-hours
UDDS	Urban Dynamometer Driving Schedule

Abbreviation	Term
UE	Upstream Emissions
UMTRI	University of Michigan Transportation Research Institute
VCR	Variable Compression Ratio
VIN	Vehicle Identification Number
VMT	Vehicle Miles Traveled
VOC	Volatile Organic Compounds
VSL	Value of a Statistical Life
VTG	Variable Turbo Geometry Technology
VTGE	Variable Turbo Geometry (Electric)
VTO	DOE Vehicle Technologies Office
VTTS	Value of Travel Time Savings
VVL	Variable Valve Lift
VVT	Variable Valve Timing
VW	Volkswagen
VWA	Volkswagen Group of America
WF	Work Factor
WTP	Willingness to Pay
ZEV	Zero Emission Vehicle

1. What is NHTSA Analyzing, and Why?

CAFE Model Files Referenced in this Chapter

Below is a list of CAFE Model Files referenced in this chapter. See Chapter 2.1.9. "Where to Find the Internal NHTSA Files?" for a full list of files referenced in this document and their respective file locations.

- CAFE Model Documentation
- Market Data Input File

The National Highway Traffic Safety Administration (NHTSA) is establishing new Corporate Average Fuel Economy (CAFE) standards for passenger cars (PC) and light trucks (LT) produced for Model Years (MYs) 2027-2031, setting forth augural CAFE standards for passenger cars and light trucks produced for model year 2032, and establishing fuel efficiency standards for heavy-duty pickup trucks and vans (HDPUVs) for model (MYs) 2030-2035. NHTSA is required by statute to set new CAFE standards for passenger cars and light trucks for each model year, and NHTSA is permitted by statute to set new fuel efficiency standards for HDPUVs.[1] NHTSA is establishing standards that increase in stringency at 2 percent per year for passenger cars produced for model years 2027-2031 (and setting forth augural standards that would increase by another 2 percent for passenger cars produced in model year 2032), at 0 percent per year for light trucks produced in model years 2027-2028 and 2 percent per year for light trucks produced in model years 2029-2031 (and setting forth augural standards that would increase by another 2 percent for light trucks produced in model year 2032). For HDPUVs, NHTSA is establishing fuel efficiency standards that increase by 10 percent per year for model years 2030-2032, and at 8 percent per year for model years 2033-2035. The regulatory alternatives representing these final stringency increases are called "PC2LT002" for passenger cars and light trucks, and "HDPUV108" for HDPUVs. These standards are also referred to throughout the rulemaking documents as the "preferred alternative" or "final standards."

This Technical Support Document (TSD) describes the supporting technical analysis that informed agency decision-makers in determining the rates of stringency increase for the final and augural CAFE standards for passenger cars and light trucks for model years 2027-2032, and for the fuel efficiency standards for HDPUVs for model years 2030-2035. This document describes the technical details about the inputs used to create models and perform simulations, that together create the analysis results discussed in the Final Regulatory Impact Assessment (FRIA).

Chapter 1 of this TSD explains how NHTSA develops footprint-based curves for the regulatory alternatives that represent different levels of possible CAFE stringency, and work-factor-based curves for the regulatory alternatives that represent different levels of possible HDPUV stringency. Chapter 1 also presents the regulatory alternatives themselves, for passenger cars and light trucks, and for HDPUVs, and explains how the CAFE Model ("the model") uses inputs to conduct the analysis.

Chapter 2 describes the development of the inputs that the model uses, including the analysis fleet, the zero emissions vehicle (ZEV) Module, compliance credits, technology effectiveness values, technology adoption and availability, technology costs, and other inputs.

Chapter 3 describes the technology options within the model.

Chapter 4 describes consumer responses to manufacturer compliance strategies, including macroeconomic assumptions that affect and describe consumer behavior, changes in fleet composition (including new vehicle sales and retirement or scrappage of existing vehicles), changes in vehicle miles traveled (VMT), and changes in fuel consumption.

Chapter 5 describes how the model simulates the environmental effects of the different regulatory alternatives, including greenhouse gas emissions effects, criteria pollutant emissions effects, and how health effects flow from those changes.

[1] 49 U.S.C. 32902.

Chapter 6 describes how the model simulates the economic effects of the different regulatory alternatives, in terms of costs and benefits that accrue to consumers and to society.

Chapter 7 describes how the model simulates the safety effects of the different regulatory alternatives.

1.1. Why Does NHTSA Conduct this Analysis?

When NHTSA develops new regulations, it generally presents an analysis that estimates the effects of such regulations, and the effects of other regulatory alternatives. These analyses derive from statutes such as the Administrative Procedure Act (APA) and National Environmental Policy Act (NEPA), from Executive Orders (such as E.O. 12866 and E.O. 13563), and from other administrative guidance (e.g., Office of Management and Budget Circular A-4). For CAFE standards, the Energy Policy and Conservation Act (EPCA) of 1975, as amended by the Energy Independence and Security Act (EISA) of 2007, contains a variety of provisions that require NHTSA to consider certain compliance elements in certain ways, and avoid considering other elements, in determining maximum feasible CAFE standards. No such restrictions exist for how NHTSA determines maximum feasible fuel efficiency standards for HDPUVs. Collectively, capturing all of these requirements and guidance elements analytically means NHTSA presents an analysis that spans a meaningful range of regulatory alternatives, quantifies a range of technological, economic, and environmental impacts, and does so in a manner that accounts for EPCA's express requirements for the CAFE program (e.g., that passenger cars and light trucks are regulated separately, and that the standard for each fleet must be set at the maximum feasible level in each model year) as well as EISA's requirements for the HDPUV program (e.g., that standards must have four years of lead time and three years of regulatory stability).

NHTSA's final rule is thus supported by, although not dictated by, extensive analysis of potential impacts of the regulatory alternatives under consideration. Together with the preamble to the final rule, this TSD, a FRIA, and a Final Environmental Impact Statement (EIS) provide an extensive and detailed enumeration of related methods, estimates, assumptions, and results. NHTSA's analysis has been constructed specifically to reflect various aspects of governing law applicable to CAFE and HDPUV standards. The analysis has been expanded and improved in response to comments received to the 2022 final rule and to the NPRM and based on additional work conducted over the last several months. Further improvements, which could not be incorporated in this final rule analysis due to timeline considerations and/or complexity, may be made in the future based on comments received and other additional work generally previewed in these rulemaking documents. The analysis for this final rule aided NHTSA in implementing its statutory obligations, including the weighing of various considerations, by reasonably informing decision-makers about the estimated effects of choosing different regulatory alternatives.

NHTSA's analysis makes use of a range of data (i.e., observations of things that have occurred), estimates (i.e., things that may occur in the future), and models (i.e., methods for making estimates). Two examples of *data* include (1) records of actual odometer readings used to estimate annual mileage accumulation at different vehicle ages and (2) CAFE compliance data used as the foundation for the "analysis fleet" containing, among other things, production volumes and fuel economy levels of specific configurations of specific vehicle models produced for sale in the United States. Two examples of *estimates* include (1) forecasts of future gross domestic product (GDP) used, with other estimates, to forecast future vehicle sales volumes and (2) the "retail price equivalent" (RPE) factor used to estimate the ultimate cost to consumers of a given fuel-saving technology, given accompanying estimates of the technology's "direct cost," as adjusted to account for estimated "cost learning effects" (i.e., the tendency that it will cost a manufacturer less to apply a technology as the manufacturer gains more experience doing so, and is, in itself, a third example of an estimate used).

NHTSA uses the CAFE Compliance and Effects Modeling System (usually shortened to the "CAFE Model" or just "the model") to estimate manufacturers' potential responses to new CAFE, carbon dioxide (CO_2) and

HDPUV standards and to estimate various impacts of those responses.[2] U.S. Department of Transportation's (DOT's) Volpe National Transportation Systems Center (often simply referred to as the "Volpe Center") develops, maintains, and applies the model for NHTSA. NHTSA has used the CAFE Model to perform analyses supporting every CAFE rulemaking since 2001. The 2016 rulemaking regarding HDPUV fuel efficiency standards, the last HDPUV rulemaking, also used the CAFE Model for analysis.

The basic design of the CAFE Model is as follows: the system first estimates how vehicle manufacturers might respond to a given regulatory scenario, and from that potential compliance solution, the system estimates what impact that response will have on fuel consumption, emissions, and economic externalities. In a highly summarized form, the following diagram shows the basic categories of CAFE Model procedures, and the sequential flow between different stages of the modeling. The diagram does not present specific model inputs or outputs or most specific procedures and model interactions. The CAFE Model Documentation accompanying this TSD presents these details.

[2] The NHTSA analysis does provide estimates for all GHGs produced, however the CO_2 compliance curves are the only aspect of the GHG standards considered during compliance modeling. Compliance with CO_2 standards is modeled in the reference baseline fleet for existing EPA GHG standareds, in this analysis that is for years thru 2026, to simulate the reference baseline behavior of the modeled fleet. NHTSA recognizes EPA may publish new final GHG standards for MYs 2027 and beyond before this final rule is published, however, those standards were not included in the reference baseline analysis, as the agencies developed their respective standards for MYs 2027 and beyond jointly.

Figure 1-1: CAFE Model Procedures and Logical Flow

Simulate Year-by-Year Compliance

- Apply technology
- Use compliance credits
- If applicable, pay civil penalties

↓

Simulate On-Road Fleet

Estimate:
- New vehicle sales
- Used vehicle scrappage
- Annual travel (VMT)

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Calculate Physical Impacts

Compute:
- Energy use
- Emissions and health effects
- Crash-related fatalities and injuries

↓

Calculate Benefits and Costs

Compute:
- Compliance costs
- Energy costs
- Environmental damages
- Crash-related losses
- Other monetized effects

More specifically, the model may be characterized as an integrated system of models. For example, one model estimates manufacturers' responses, another estimates resultant changes in total vehicle sales, and still another estimates resultant changes in fleet turnover (i.e., scrappage). A regulatory scenario involves specification of the form, or shape, of the standards (e.g., linear attribute-based standards), scope of passenger car, light truck, and/or HDPUV regulatory classes, and stringency of the CAFE and/or fuel efficiency standards for each model year to be analyzed. Additionally, and importantly, the model does not *determine* the form or stringency of the standards. Instead, the model applies *inputs* specifying the form and stringency of standards to be analyzed and produces *outputs* showing the impacts on the manufacturers working to meet those standards. Those outputs then become the basis for comparing between different potential stringency levels.

Manufacturer compliance simulation and the ensuing effects estimation, collectively referred to as compliance modeling, encompass numerous subsidiary elements. Compliance simulation begins with a detailed user-provided[3] initial forecast of the vehicle models offered for sale during the simulation period. The compliance

[3] Because the CAFE Model is publicly available, anyone can develop their own initial forecast (or other inputs) for the model to use. The DOT-developed Market Data Input File that contains the forecast used for this final rule is available on NHTSA's website at https://www.nhtsa.gov/laws-regulations/corporate-average-fuel-economy.

simulation then attempts to bring each manufacturer into compliance with the applicable standards[4] defined by the regulatory scenario contained within an input file developed by the user.

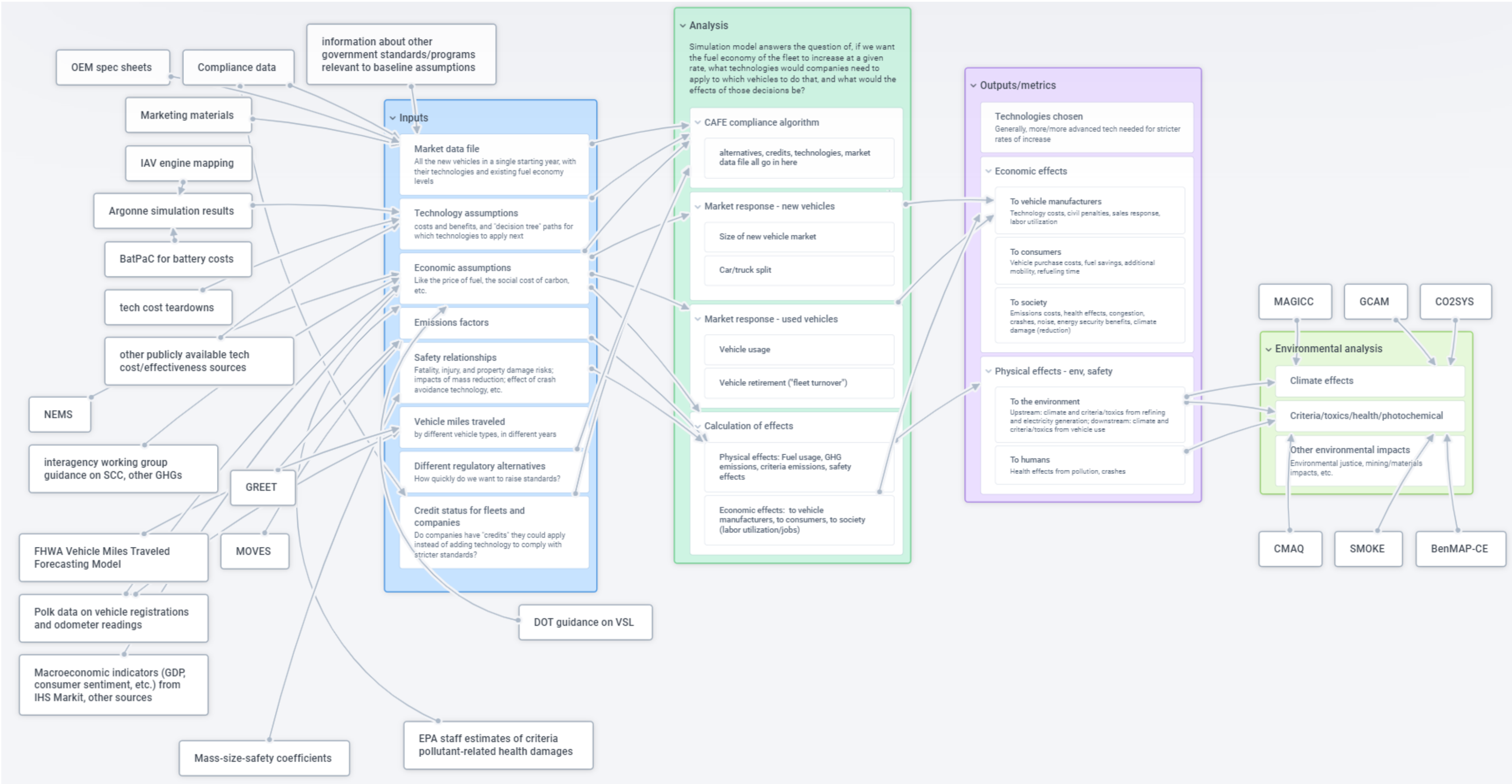
Estimating impacts involves calculating resultant changes in new vehicle costs, estimating a variety of costs (e.g., for fuel) and effects (e.g., CO_2 emissions from fuel combustion) occurring as vehicles are driven over their lifetimes before eventually being scrapped, and estimating the monetary value of these effects. Estimating impacts also involves consideration of consumer responses – e.g., the impact of vehicle fuel economy, operating costs, and vehicle price on consumer demand for passenger cars, light trucks, and HDPUVs. Both basic analytical elements involve the application of many analytical inputs. Many of these inputs are developed *outside* the model and not *by* the model.

NHTSA also uses the U.S. Environmental Protection Agency's (EPA's) Motor Vehicle Emissions Simulator (MOVES) model to estimate "vehicle" or "downstream" emission factors for criteria pollutants,[5] and uses four DOE and DOE-sponsored models to develop inputs to the CAFE Model, including three developed and maintained by DOE's Argonne National Laboratory (ANL). The agency uses the DOE Energy Information Administration's (EIA's) National Energy Modeling System (NEMS) to estimate fuel prices,[6] uses Argonne's Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET) model to estimate emissions rates from fuel production and distribution processes,[7] and uses Argonne's Battery Manufacturing Cost Estimation (BatPaC) tool to estimate electric and hybrid vehicle battery costs.[8] DOT also sponsored DOE/Argonne to use Argonne's Autonomie full-vehicle modeling and simulation system to estimate the fuel economy impacts for over a million combinations of technologies and vehicle types.[9] We adapted the same tools, including updating initial inputs and data, for the HDPUV portions of the analysis.[10] Other chapters in this TSD and discussion in the accompanying FRIA describe details of the agency's use of these models. In addition, as discussed in the Final EIS accompanying this final rule, DOT relied on a range of climate models to describe impacts on climate, air quality, and public health. The Final EIS discusses and describes the use of these models.

The CAFE Model, therefore, serves as a "hub" that connects and holds together a wide range of inputs, processes, and other models that all inform DOT's analysis, and that, in turn, provides model results underlying the Final EIS accompanying this final rule. Though not exhaustive, the diagram on the following page shows most of the important connections between different elements of DOT's analysis.

[4] With appropriate inputs, the model can also be used to estimate impacts of manufacturers' potential responses to new CO_2 standards and to California's ZEV program.
[5] See http://www.epa.gov/moves. This final rule uses version MOVES4, available at https://www.epa.gov/moves/latest-version-motor-vehicle-emission-simulator-moves.
[6] See https://www.eia.gov/outlooks/aeo/info_nems_archive.php. This final rule uses fuel prices estimated using the AEO 2023 version of NEMS. See https://www.eia.gov/outlooks/aeo/.
[7] Information regarding GREET is available at https://greet.es.anl.gov/. This final rule uses the 2022 version of GREET.
[8] Argonne National Laboratory. BatPaC: Battery Manufacturing Cost Estimation Available at: https://www.anl.gov/tcp/batpac-battery-manufacturing-cost-estimation. (Accessed: Feb 7, 2023).
[9] As part of the Argonne simulation effort, individual technology combinations simulated in Autonomie were paired with Argonne's BatPaC model to estimate the battery cost associated with each technology combination based on characteristics of the simulated vehicle and its level of electrification. Information regarding Argonne's BatPaC model is available at https://www.anl.gov/cse/batpac-model-software. In addition, the impact of engine technologies on fuel consumption, torque, and other metrics was characteritzed using GT-POWER simulation modeling in combination with other engine modeling that was that was conducted by IAV Automotive Engineering, Inc. (IAV) and South West Research Institute (SWRI). The engine characterization "maps" resulting from this analysis were used as inputs for the Autonomie full-vehicle simulation modeling. Information regarding GT-POWER is available at https://www.gtisoft.com/gt-power/.
[10] Specific details on the input modifiications to support the HDPUV analysis are discussed under their associated chapters.

Figure 1-2: Key Elements of DOT's Analysis, from 2022 TSD



To prepare for the analysis that supported the notice for this rule, DOT has continued its ongoing effort to refine and expand the CAFE Model. Since the 2022 final rule, DOT has made the following changes to the CAFE Model and inputs, including:

- Update analysis fleet from MY2020 to MY2022
- Addition of the HDPUV fleet and supporting analyses, added to account for manufacturers' responses to applicable fuel efficiency and CO_2 standards, including:
    - New HDPUV-specific technologies, costs, and fuel efficiency improvement assumptions.
    - New HDPUV technology classes (Pickup2b, Van2b, Pickup3, and Van3).
    - New HDPUV engine technology classes (ranging from 4C1B to 10C2B for Dual Overhead Camshaft (DOHC), Single Overhead Cam (SOHC), and OHV variants).
    - New HDPUV vehicle styles (WorkTruck, WorkVan, FleetSUV) beyond those previously included (Chassis Cab, Cutaway) and the removal of one prior vehicle style (Large Pickup).
    - Revised HDPUV-related compliance calculations of fuel efficiency standards and ratings, calculated and reported in mpg space and gallons/100-mile space. And HDPUV fuel consumption credits calculated and reported in gallons, based on the useful life value assumption.
    - New target function and coefficients applicable to the HDPUV CO_2 standards.
    - Allowing use of credits (via carry-forward) to offset shortfalls to the manufacturers' HDPUV fuel efficiency and CO_2 ratings during standard setting years.
    - Allowing unrestricted application of plug-in hybrid electric vehicle (PHEVs), battery electric vehicles (BEVs), and fuel cell vehicles (FCEVs) to the HDPUV fleet during standard setting years, as is allowed by the governing statute.
    - Accounting for additional HDPUV-specific categories of downstream health related impacts and emission damage costs attributed to criteria air pollutants (SO_X, NO_X, and $PM_{2.5}$).
    - Revising the sales and scrappage models to account for the HDPUV fleet.
    - Incorporating the accounting for the ZEV mandates applicable in California and the Section 177 states for the HDPUV fleet.
- Inclusion of updated assumptions for light-duty vehicle technologies, costs, and fuel efficiency improvement and removing obsolete technologies: engine friction reduction (EFR), advanced diesel engine with improvements and advanced cylinder deactivation (DSLIAD), manual transmissions, AT6L2, electric power steering (EPS), improved accessories (IACC), Low Drag Brakes (LDB), secondary axle disconnect (SAX), and some variants of engines and P2 hybrid pairings.
- Allowing direct user input of additional parameters, including:
    - Petroleum equivalency factor (PEF).
    - Share of total refueling events to consider when calculating benefits attributed to the refueling time cost.
    - Whether application of PHEV, BEV, or FCEV technologies is permitted during the standard setting model years. This is not applicable to the HDPUV fleet or to vehicles designated as ZEV candidates. For the current analysis of the CAFE light-duty fleet, NHTSA allowed application of PHEVs while disallowing application of BEVs and FCEVs during the standard setting years.[11]
- Updating calculation of implicit opportunity cost to exclude a portion of vehicle sales assumed to be used for commercial applications. For the central analysis, NHTSA did not implement this added feature of the model, but produced multiple sensitivity analyses that varied this parameter for the HDPUV fleet.
- Procedures added for estimating and reporting:
    - the commercial operator implicit opportunity cost, using the same assumptions of commercial use vs consumer use, as above.
    - vehicular $PM_{2.5}$ emissions attributed to brake and tire wear (BTW).
- Allowing the use of credits (via transfers and carry-forward) to offset shortfalls to the manufacturers' CO_2 ratings during standard setting years.

[11] See CAFE Model Documentation for a discussion of 'Standard Setting' limitations on the model.

- Inclusion of expanded accounting of Federal incentives as outlined in the Inflation Reduction Act (IRA); propagating this change within relevant modules and including these incentives in the "effective cost" metric used when simulating manufacturers' potential application of fuel-saving technologies.
- Expanding the accounting for manufacturer responses to the ZEV mandates applicable in California and the Section 177 states for the light-duty fleet (and manufacturer commitments to deploy electric vehicles consistent with the targets of the Advanced Clean Cars II program), differentiating between credits earned prior to model year 2026 and starting in model year 2026. Revising the model allows the simulation of compliance with much higher ZEV targets set by the states.
- Incorporating new procedures and methodologies for technology inheriting between platforms, engines, and transmissions and their respective vehicle "users."
- Expanding procedures for estimating new vehicles sales and the shares of passenger car and light truck fleets during future model years in the reference baseline and action alternative scenarios:
    - Incorporating revisions to allow direct specification of coefficients for estimating the nominal forecast of sales under the reference baseline scenario.
    - Including an option to use a user-defined annual forecast of light-duty and HDPUV sales and a user-defined annual forecast of the portion of the light-duty fleet that will be passenger cars in the reference baseline scenario.
    - Including a user-selectable option for propagating reference baseline computed car shares to all action alternatives or allowing the car shares for each alternative to be adjusted based on the differences in regulatory costs, vehicle and battery tax credits, and fuel savings occurring between alternatives and between car and truck fleets.
- Inclusion of new coefficients for the VMT model used when evaluating the light-duty fleet only.
- Updated input parameters for the safety model.
- Updating and expanding model reporting capabilities:
    - reporting of additional metrics such as vehicle and battery tax credits.
    - options to split vehicle and diagnostic reports by scenario.

In response to feedback, interagency meetings, comments from stakeholders, as well as continued development, DOT has made additional changes to the CAFE Model for the final rule. Since the 2023 NPRM, DOT has made the following changes to the CAFE Model and inputs, including:

- Updated battery costs for electrified technologies.
- Updated ZEV State shares, credit values and projected ZEV requirements.
- Reclassified Rivian and Ford vehicles from HDPUV to light-duty based official cert data submission.
- Allow the user to directly input air conditioning (AC) efficiency, AC leakage and off cycle credit limits for each model year, separately for conventional vehicles and electric vehicles.
- All references to '2b3' regulatory class have been changed to 'HDPUV'.
- The model will no longer apply road load-improving technology to electric vehicles as part of the standard setting constraints.
- The model will no longer apply road load-improving technology to electric vehicles to achieve compliance with GHG rules.
- Updating and expanding model reporting capabilities:
    - Outputs now show battery costs, non-battery tech costs, and AC/OC costs split, as well as "total" tech costs.
    - Added Minimum Domestic Passenger Car (MDPC) output for domestic passenger cars.
    - Expand reporting of AC and off-cycle credits in the compliance report to split columns into "CAFE" and "CO_2" values.
- Updated IRA Tax credit implementation:
    - The IRA tax credit is now applied in model year 2023 instead of model year 2024 and ends in model year 2032 instead of model year 2033.

- Model now has a toggle to zero out A/C and O/C costs rather than show cost savings when these are removed.
- Updated input factors for economic models.
- Updated input factors for the safety models.
- Updated emission modeling.
    - Updated upstream factors.
    - Set N_2O emissions to a global count, consistent with other GHG.

These changes reflect DOT's long-standing commitment to ongoing refinement of its approach to estimating the potential impacts of new CAFE and HDPUV standards, and, since the early 2000s, refining the CAFE Model to make such estimates, as shown in Table 1-1.

Table 1-1: CAFE Model and Inputs Refinement Milestones

2001-2002	• Inception and early development • Application to all manufacturers
2003	• Accounting for redesign cadence
2004-2006	• Integration of compliance, effects, and benefit-cost methods • Accounting for shared engines and transmissions • Representation of attribute-based LT standards • Application of social cost of carbon • Maximization of estimated net benefits • Probabilistic uncertainty analysis (Monte Carlo method)
2007-2009	• Attribute-based PC standards • "Synergy" factors to adjust MPG estimates for technology pairings
2010	• Flex Fuel Vehicle credits • Accounting for manufacturers' multiyear product planning

2011-2012	• Initial use of full vehicle simulations
	• Accounting for BEV and PHEV charging
	• Applying technology-specific estimates of changes in consumer value
	• New methods to estimate:
	  ○ generation and use of CAFE credits
	  ○ potential for market-driven fuel economy increases
	  ○ changes in highway fatalities due to changes in vehicle mass

2013-2016	• Wide application of full vehicle simulation • Accounting for shared vehicle platforms • Attribute-based standards for heavy-duty (class 2b and 3) pickups and vans

2017-2020	• Simulation of compliance with attribute-based CO_2 standards[12]
	• Refinements to compliance credit calculations
	• New modules to estimate:
	  ○ impacts on new vehicle sales and used vehicle retirement
	  ○ changes in annual mileage accumulation (VMT)
	  ○ employment effects
	  ○ health effects of criteria pollutant emissions

[12] This capability is used in the calcuation of reference baseline fleet behavior.

2021	• Inclusion of 400- and 500-mile BEVs and HCR engines with cylinder deactivation
	• Accounting for CAFE and CO_2 standards jointly[13] (expanding existing capability to estimate separately)
	• Incorporating:
	  ○ ZEV mandates applicable in California and the "Section 177" states
	  ○ California "Framework" agreement with specific OEMs
	• Estimating impacts and monetized damages of highway vehicle crashes that do not result in fatalities

2022-2023	• Addition of HDPUV, and required updates across entire model
	• Update technologies considered in the analysis
	  ○ Addition of HCRE, HCRD and updated Diesel technology models
	  ○ Removal of EFR, DSLIAD, manual transmissions, AT6L2, EPS, IACC, LDB, SAX, and some P2 combinations.
	• User control of additional input parameters
	• Updated ZEV Mandate modeling approach
	• Expanded accounting for Federal Incentives, such as the IRA
	• Expanded procedures for estimating new vehicle sales and fleet shares
	• VMT coefficient updates
	• Additional output values and options

2023-2024	• Expanded Off-Cycle and A/C efficiency capability in the model to allow adoption by ICE vehicles and electrified vehicles independently, and apply independent limits • Expanded ZEV framework to allow adoption on per model year basis and pooling of credits • Updated modeling of application of road load technologies to ZEVs during standard setting years and when considered for GHG compliance • Added capability to model HDPUV fuel agnostic standards • Changed 2b3 references to HDPUV throughout all the inputs • Added additional output values and options

Because the CAFE Model simulates a wide range of actual constraints and practices related to automotive engineering, planning, and production, such as common vehicle platforms, sharing of engines among different vehicle models, and timing of major vehicle redesigns, the analysis produced by the CAFE Model provides a transparent and realistic basis to show pathways manufacturers could follow over time in applying new technologies, which helps better assess impacts of potential future standards. Considering the technological heterogeneity of manufacturers' current product offerings, and the wide range of ways in which the many fuel-economy- and efficiency-improving technologies included in the analysis can be combined, the CAFE Model has been designed to use inputs that provide an estimate of the fuel economy or efficiency achieved for many tens of thousands of different potential combinations of fuel-saving technologies. Across the range of technology classes encompassed by the analysis fleet, this analysis involves more than a million such estimates. While the CAFE Model requires no specific approach to developing these inputs, the National Academy of Sciences (NAS) has recommended, and stakeholders have commented, that full-vehicle simulation provides the best balance between realism and practicality. DOE/Argonne has spent several years developing, applying, and expanding means to use distributed computing to exercise its Autonomie full-vehicle modeling and simulation tool over the scale necessary for realistic analysis of CAFE and HDPUV standards. This scalability and related flexibility (in terms of expanding the set of technologies to be simulated) makes Autonomie well-suited for developing inputs to the CAFE Model.

In addition, DOE/Argonne's Autonomie also has a long history of development and widespread application by a wide range of users in government, academia, and industry. Many of these users apply Autonomie to inform funding and design decisions. These real-world exercises have contributed significantly to aspects of

[13] *Id.*

Autonomie important to producing realistic estimates of fuel economy and efficiency levels, such as estimation and consideration of performance, utility, and drivability metrics (e.g., towing capability, shift busyness, frequency of engine on/off transitions.) This steadily-increasing realism has, in turn, steadily increased confidence in the appropriateness of using Autonomie to make significant investment decisions. Notably, DOE uses Autonomie for analysis supporting budget priorities and plans for programs managed by its Vehicle Technologies Office (VTO).

Like any model, both Autonomie and the CAFE Model benefit from ongoing refinement. Nevertheless, NHTSA is confident that the combination of models in the most recent iteration produces a realistic characterization of the potential impacts of potential new standards. The majority of stakeholders that have supported the agency's reliance on the DOE/Argonne Autonomie tool and CAFE Model have noted not only technical reasons to use these models, but also other reasons such as efficiency, transparency, and ease with which outside parties can utilize models and replicate the agency's analysis.

This analysis exercises the CAFE Model in a manner that explicitly accounts for the fact that vehicle manufacturers face the combination of CAFE and/or HDPUV standards, existing EPA greenhouse gas (GHG) standards, and state ZEV mandates applicable during the (NHTSA) rulemaking time frame. Additionally, vehicle manufacturers have committed to deploy additional electric vehicles consistent with state programs that have been adopted but not granted a waiver of Clean Air Act preemption. These regulations have important interactions affecting strategies a manufacturer could use to comply with each of the above, and NHTSA believes, as discussed at more length in the preamble, that it is important for agency decision-makers to be as informed as possible about the effects of the regulatory landscape in which future CAFE compliance would be occurring.

As explained, the analysis is designed to reflect several statutory and regulatory requirements applicable to CAFE and HDPUV standard setting. The Energy Policy and Conservation Act of 1975 (EPCA) contains several requirements governing the scope and nature of CAFE standard setting. Among these, some have been in place since EPCA was first signed into law in 1975, and some were added in 2007, when Congress passed EISA and amended EPCA. The authority for HDPUV standards that came with EISA included considerably fewer such requirements. The Clean Air Act (CAA), as discussed elsewhere, provides EPA with very broad authority under Section 202(a), and does not contain EPCA/EISA's prescriptions. In some cases, in the interest of harmonization, NHTSA has created some additional flexibilities by regulation not expressly included or prohibited by EPCA/EISA in order to harmonize better with some of EPA's programmatic decisions. EPCA/EISA requirements regarding the technical characteristics of CAFE and HDPUV standards and the analysis thereof include, but are not limited to, the following, and the analysis reflects these requirements as summarized:

<u>Corporate Average Standards</u>: 49 U.S.C. 32902 requires that standards apply to the average fuel economy (which, for HDPUVs, is fuel efficiency) levels achieved by each corporation's fleets of vehicles produced for sale in the United States.[14] EPA has adopted a similar approach under Section 202(a) of the CAA in the interest of harmonization. The CAFE Model calculates the CAFE fuel economy, HDPUV fuel efficiency, and CO_2 levels of each manufacturer's fleets based on estimated production volumes and characteristics, including fuel economy/efficiency levels, of distinct vehicle models that could be produced for sale in the United States.[15]

<u>Separate Standards for Passenger Cars, Light Trucks, and HDPUVs</u>: 49 U.S.C. 32902 requires the Secretary of Transportation (the Secretary) to set CAFE standards separately for passenger cars and light trucks, and also to set separate standards for HDPUVs. EPA has adopted a similar approach under Section 202(a) of the CAA. The CAFE Model accounts separately for passenger cars, light trucks, and HDPUVs, including differentiated standards and compliance.

[14] This differs from safety standards and traditional emissions standards, which apply separately to each vehicle. For example, every vehicle produced for sale in the United States must, on its own, meet all applicable Federal motor vehicle safety standards (FMVSS), but no vehicle produced for sale must, on its own, meet Federal fuel economy or efficiency standards. Rather, each manufacturer is required to produce a mix of vehicles that, taken together, achieve an average fuel economy or efficiency level no less than the applicable minimum level.
[15] The NHTSA analysis does provide estimates for all GHGs produced, however the CO_2 compliance curves are the only aspect of the GHG standards considered during compliance modeling.

Attribute-Based Standards: 49 U.S.C. 32902 requires the Secretary to define CAFE (passenger car and light truck) standards as mathematical functions expressed in terms of one or more attributes related to fuel economy. This means that for a given manufacturer's fleet of vehicles produced for sale in the United States in a given regulatory class and model year, the applicable minimum CAFE requirement (i.e., the numerical value of the requirement) is computed based on the applicable mathematical function, and the mix and attributes of vehicles in the manufacturer's fleet. While this requirement is not express for HDPUVs, NHTSA also sets attribute-based standards for that category of vehicles. EPA has also adopted attribute-based standards under its broad CAA Section 202(a) authority in its current GHG standards. The CAFE Model accounts for such functions and vehicle attributes explicitly.

Separately Defined Standards for Each Model Year: 49 U.S.C. 32902 requires the Secretary to set CAFE standards (separately for passenger cars and light trucks[16]) and fuel efficiency standards for HDPUVs at the maximum feasible levels in each model year. While passenger car and light truck standards must be set separately for each model year, HDPUV standards must be set in 3-year tranches, although they may vary within a tranche. CAA Section 202(a) allows EPA to establish CO_2 standards separately for each model year, and EPA has chosen to do this in the previous vehicle CO_2 standard-setting rules. The CAFE Model represents each model year explicitly, and accounts for the production relationships between model years.[17]

Separate Compliance for Domestic and Imported Passenger Car Fleets: 49 U.S.C. 32904 requires the EPA Administrator to determine CAFE compliance separately for each manufacturer's fleets of domestic passenger cars and imported passenger cars,[18] which manufacturers must consider as they decide how to improve the fuel economy of their passenger car fleets, if they build both domestic and imported passenger cars. EPA does not have a similar requirement for CO_2 standard compliance. The CAFE Model accounts explicitly for this requirement when simulating manufacturers' potential responses to CAFE standards, and the model combines any given manufacturer's domestic and imported cars into a single fleet instead when simulating that manufacturer's potential response to CO_2 standards.

Minimum CAFE Standards for Domestic Passenger Car Fleets: 49 U.S.C. 32902 requires that domestic passenger car fleets also meet a minimum CAFE standard, which is calculated as 92 percent of the industry-wide average level required under the applicable attribute-based CAFE standard, as projected by the Secretary at the time the standard is promulgated. EPA's GHG program does not contain a similar requirement. The CAFE Model accounts explicitly for this requirement for CAFE standards and sets this requirement aside for CO_2 standards.

Civil Penalties for Noncompliance: 49 U.S.C. 32912 (and implementing regulations) prescribes a rate (in dollars per tenth of a mpg) at which the Secretary is to levy civil penalties if a manufacturer fails to comply with a CAFE standard for a given fleet in a given model year, after considering available credits. While NHTSA does not consider credit availability in determining maximum feasible standards, some manufacturers have historically demonstrated a willingness to pay civil penalties rather than achieving full numerical compliance across all fleets.[19] The CAFE Model calculates civil penalties for CAFE shortfalls and provides means to estimate that a manufacturer might stop adding fuel-saving technologies once continuing to do so would be effectively more "expensive" (after accounting for fuel prices and buyers' willingness to pay for fuel economy) than paying civil penalties. This capability can be implemented or not at the user's choice. In contrast, the CAA does not authorize the EPA Administrator to allow manufacturers to sell noncompliant fleets and pay civil penalties; manufacturers who have chosen to pay civil penalties for CAFE compliance instead have tended to employ EPA's more-extensive programmatic flexibilities to meet EPA's CO_2 emissions standards. Thus, the CAFE Model does not allow civil penalty payment as an option for CO_2 standards.[20] For

[16] 49 U.S.C. chapter 329 uses the term "non-passenger automobiles," while NHTSA uses the term "LTs" in its CAFE regulations. The terms' meanings are identical.
[17] For example, a new engine first applied to a given vehicle model/configuration in MY 2030 will most likely be retained in MY 2031 of that same vehicle model/configuraiton, in order to reflect the fact that manufacturers do not apply brand-new engines to a given vehicle model every single year. The CAFE Model is designed to account for this reality, while still respecting applicable statutory constraints.
[18] A passenger car is considered domestic or import based on the definitions provided in 49 U.S.C. 32904.
[19] NHTSA does not assume willingness to pay civil penalties for manufacturers who have commented publicly that they will not pay civil penalties in the rulemaking time frame.
[20] Compliance with CO_2 standards are includinced in our model as part of the overall regulatory landscape considered for setting maximum feasible CAFE and HDPUV Standards.

NHTSA's HDPUV standards, the model also does not allow civil penalty payment because manufacturers have not exercised this option in the real world.

Dual-Fueled and Dedicated Alternative Fuel Vehicles: For purposes of calculating CAFE levels used to determine passenger car and light truck fleet compliance, 49 U.S.C. 32905 and 32906 specify methods for calculating the fuel economy levels of vehicles operating on alternative fuels to gasoline or diesel fuels.[21] The CAFE Model can account for these requirements explicitly for each relevant vehicle model. However, 49 U.S.C. 32902 also prohibits consideration of the fuel economy of dedicated Alternative Fuel Vehicle (AFV) models (or the non-gasoline calculated fuel economy of dual-fueled AFVs) when NHTSA determines what levels of passenger car and light truck CAFE standards are maximum feasible for the model years at issue in a rulemaking. The CAFE model therefore has an option to be run in a manner that excludes the additional application of dedicated AFV technologies in model years for which maximum feasible standards are under consideration, and to limit the consideration of dual-fueled AFVs' fuel economy to only their gasoline or diesel operation. We run the model with this limitation when performing the analysis that informs the standard ultimately chosen. The CAFE Model can also be run without this analytical constraint, and we do run it this way to ensure that the environmental impacts of this action are considered pursuant to NEPA. In evaluating the potential fuel efficiency standards for HDPUVs, per regulation, the CAFE Model considers only the gasoline or diesel fuel as counting toward the fuel use. As a result, vehicles that run completely on alternative fuels, such as fully electric vehicles (EVs), currently receive a 0 g/100 mile value for purposes of compliance in the HDPUV fleet. CAA Section 202(a) does not similarly require EPA to avoid consideration of dedicated AFVs when setting CO_2 standards, or to limit consideration of dual-fueled AFVs. The CAFE model thus accounts for dual-fueled and dedicated AFVs when simulating manufacturers' potential responses to CO_2 standards.

Creation and Use of Compliance Credits: 49 U.S.C. 32903 provides that manufacturers may earn CAFE "credits" by achieving a CAFE level beyond that required of a given fleet in a given model year and specifies how these credits may be used to offset the amount by which a different fleet falls short of its corresponding requirement. These provisions allow credits to be "carried forward" and "carried back" between model years, transferred between regulated classes (domestic passenger cars, imported passenger cars, and light trucks), and traded between manufacturers. However, credit use is also subject to specific statutory limits. For example, CAFE compliance credits can be carried forward a maximum of five model years and carried back a maximum of three model years. Also, EPCA/EISA caps the amount of credit that can be transferred between a manufacturer's fleets and prohibits manufacturers from applying traded or transferred credits to offset a failure to achieve the minimum standard for domestic PCs. No such statutory restrictions exist for HDPUVs, which may also earn credits as set forth in 49 CFR 535.7, and which implements certain restrictions like credit lifespan and prohibiting transfers. The CAFE Model explicitly simulates manufacturers' potential use of credits carried forward from prior model years or transferred from other fleets.[22]

49 U.S.C. 32902 prohibits consideration of manufacturers' potential application of CAFE compliance credits when setting maximum feasible CAFE standards for passenger cars and light trucks, although there is no

[21] In some cases (like for "flex-fuel vehicles" that are capable of running on E85), the statute provides no further direction after MY 2020, and NHTSA and EPA have developed regulatory provisions to address the gap.

[22] The CAFE Model does not explicitly simulate the potential that manufacturers would carry CAFE or HDPUV credits back (i.e., borrow) from future MYs, or acquire and use CAFE or HDPUV compliance credits from other manufacturers. At the same time, because EPA has currently elected not to limit credit trading or transferring (at least between PCs and LTs), the CAFE Model can be exercised in a manner that simulates unlimited (a.k.a. "perfect") CO_2 compliance credit trading throughout the industry (or, potentially, within discrete trading "blocs"). NHTSA believes that there is significant uncertainty in how manufacturers may choose to employ these particular flexibilities in the future: for example, while it is reasonably foreseeable that a manufacturer who over-complies in one year may "coast" through several subsequent years relying on that prior improvement rather than continuing to make technology improvements year after year, it is harder to assume with confidence that manufacturers will rely on future technology investments to offset prior-year shortfalls, or whether/how manufacturers will trade credits with market competitors rather than making their own technology investments. Historically, carry-back and trading have been much less utilized than carry-forward, for a variety of reasons including higher risk and preference not to 'pay competitors to make fuel economy improvements we should be making' (to paraphrase one manufacturer), although NHTSA recognizes that carry-back and trading are used more frequently when standards increase more rapidly in stringency. Given the uncertainty just discussed, and given also the fact that the agency has yet to resolve some of the analytical challenges associated with simulating use of some of these flexibilities, the agency considers borrowing and trading to involve sufficient risk that it is prudent to support this final rule with analysis that sets aside the potential that manufacturers could come to depend widely on borrowing and trading. While compliance costs in real life may be somewhat different from what is modeled today as a result of this analytical decision, that is broadly true no matter what, given constraints on consideration of credit availability in determining maximum feasible standards, and the agency does not believe that the difference would be so great that it would change the policy outcome. Furthermore, a manufacturer employing a trading strategy would presumably do so because it represents a lower-cost compliance option. Thus, the estimates derived from this modeling approach are likely to be conservative in this respect, with real-world compliance costs possibly being lower.

such prohibition for setting HDPUV standards. The CAFE Model can be operated in a manner that excludes the application of CAFE credits for a given model year under consideration for standard setting, and we run the model with this restriction when performing our standard-setting analysis for the CAFE standards for passenger cars and light trucks. CAA 202(a) does not preclude the EPA Administrator from adopting analogous provisions. With some exceptions, EPA's reference baseline regulations limit the "life" of compliance credits from most model years to 5 years, and limit borrowing to 3 years, but do not limit transfers (between a manufacturer's fleets) or trades (between manufacturers) of compliance credits. The CAFE Model accounts for the absence of limits on transfers of CO_2 standards. Insofar as the CAFE Model can be exercised in a manner that simulates trading of CO_2 compliance credits, such simulations treat trading as unlimited.[23]

Statutory Basis for Stringency: 49 U.S.C. 32902 requires the Secretary to set CAFE standards for passenger cars and light trucks at the maximum feasible levels, considering technological feasibility, economic practicability, the need of the U.S. to conserve energy, and the impact of other motor vehicle standards of the Government on fuel economy. HDPUV standards must also be maximum feasible, considering appropriateness, cost-effectiveness, and technological feasibility. EPCA/EISA authorizes the Secretary to interpret these factors, and as the Department's interpretation has evolved, NHTSA has continued to expand and refine its qualitative and quantitative analysis to account for these statutory factors. For example, the Autonomie simulations reflect the agency's judgment that it would not be economically practicable, appropriate, or cost-effective for a manufacturer to "split" an engine shared among many vehicle model/configurations into myriad versions each optimized to a single vehicle model/configuration.

National Environmental Policy Act: In addition, the agency is issuing an EIS that documents the estimated impacts of regulatory alternatives under consideration. The EIS accompanying this final rule documents changes in emission inventories as estimated using the CAFE Model, but also documents corresponding estimates – based on the application of other models documented in the EIS – of impacts on the global climate, on tropospheric air quality, and on human health.

Other Aspects of Compliance, including ZEV Mandates: Beyond these statutory requirements applicable to DOT and/or EPA are several specific factors also considered.

The CAFE Model can simulate manufacturers' compliance with ZEV mandates applicable in California and Section 177 states. Additionally, the model can simulate manufacturer commitments to deploy electric vehicles consistent with state programs that have been adopted but not granted a waiver of Clean Air Act preemption. This approach involves identifying specific vehicle model/configurations that could be replaced with PHEVs or BEVs, and immediately making these changes in each model year, before beginning to consider the potential that other technologies could be applied toward compliance with CAFE or CO_2 standards.

Several technical characteristics of CAFE and/or CO_2 regulations are also relevant to the construction of this analysis. For example, through certain model years, EPA has defined procedures for calculating average CO_2 levels, and has revised procedures for calculating CAFE levels, to reflect manufacturers' application of "OC" technologies that increase fuel economy. Similar procedures are available for HDPUV compliance. Although too little information is available to account for these provisions explicitly in the same way that the agency has accounted for other technologies, the CAFE Model does include and makes use of inputs reflecting the agency's expectations regarding the extent to which manufacturers may earn such credits, along with estimates of corresponding costs. Similarly, the CAFE Model includes and makes use of inputs regarding credits EPA has elected to allow manufacturers to earn toward CO_2 levels (not CAFE) based on the use of AC refrigerants with lower global warming potential, or on the application of technologies to reduce refrigerant leakage. In addition, EPA has elected to provide that through certain model years, manufacturers may apply "multipliers" to plug-in hybrid EVs, BEVs, fuel cell vehicles, and hydrogen vehicles, such that when calculating a fleet's average CO_2 levels (not CAFE), the manufacturer may, for example, "count" each EV twice.[24] The CAFE Model accounts for these multipliers, based on current regulatory provisions or on

[23] To avoid making judgments about possible future trading activity, when exercising the model in this way, the agency combines all manufacturers into a single entity, so that the most cost-effective choices are made for the fleet as a whole. Compliance with CO_2 standards are included in our model as part of the overall regulatory landscape considered for setting maximum feasible CAFE and HDPUV standards.
[24] The EPA incentives are considered in reference baseline calculations simulating fleet behavior up to standard setting years (2022-2026).

alternative approaches. Although these are examples of regulatory provisions that arise from the exercise of discretion rather than specific statutory mandate, they can materially impact outcomes.

Besides the updates to the model described above, any analysis of regulatory actions that will be implemented several years in the future, and whose benefits and costs accrue over decades, requires many assumptions. Over such time horizons, many, if not most, of the relevant assumptions in such an analysis are inevitably uncertain. It is natural that each successive CAFE and HDPUV analysis should update assumptions to reflect better the current state of the world and the best current estimates of future conditions.

As discussed in the list provided above, assumptions have been updated since the 2022 final rule, and the 2023 NPRM, for this final rule. While NHTSA would have made these updates as a matter of course, we note that the ongoing recovery from the global Coronavirus disease of 2019 (COVID-19) pandemic, the war in Ukraine and the economic consequences of both of those events have been profoundly disruptive, including ways directly material to major analytical inputs such as fuel prices, GDP, vehicle production and sales, and highway travel. For this analysis, NHTSA continues to use a model year 2022 reference for passenger cars and light trucks and an updated HDPUV analysis fleet (the last HDPUV analysis fleet was built in 2016). NHTSA has also updated estimates of manufacturers' compliance credit banks, updated fuel price projections to reflect the U.S. Energy Information Administration's (EIA's) 2023 Annual Energy Outlook (AEO), updated projections of GDP and related macroeconomic measures, updated projections of future highway travel, and updated estimates and assumptions used to compute social costs (SCs) and benefits related to vehicle use and fuel consumption. (e.g., costs related to traffic safety). These and other updated analytical inputs are discussed in detail in the remainder of this TSD.

1.2. What Is NHTSA Analyzing?

1.2.1. Attribute-Based Standards

Passenger car, light truck, and HDPUV standards are all attribute-based. As in the CAFE and CO_2 rulemakings in 2010, 2012, 2020, and 2022, NHTSA is setting CAFE standards defined by a mathematical function of vehicle footprint, which has an observable correlation with fuel economy. For our purposes, a vehicle's footprint is defined, per 49 CFR 523.2, as the vehicle's track width multiplied by the vehicle's wheelbase and rounded to the nearest 1/10 foot squared. EPCA, as amended by EISA, expressly requires that CAFE standards for passenger cars and light trucks be based on one or more vehicle attributes related to fuel economy and be expressed in the form of a mathematical function.[25] Thus, the final standards, and regulatory alternatives, take the form of fuel economy targets expressed as functions of vehicle footprint,[26] that are separate for passenger cars and light trucks. Chapter 1.2.3 below discusses NHTSA's continued reliance on footprint as the relevant attribute for passenger cars and light trucks in this final rule.

Under the footprint-based standards, the function defines a fuel economy performance target for each unique footprint combination within a passenger car or light truck model type. Using the functions, each manufacturer will have a CAFE average standard for each year that is almost certainly unique to each of its fleets,[27] based upon the footprints and production volumes of the vehicle models produced by that manufacturer. A manufacturer will have separate footprint-based standards for passenger cars and for light trucks, consistent with 49 U.S.C. 32902(b)'s direction that NHTSA must set separate standards for passenger cars and for light trucks. The functions are mostly sloped, so that generally, larger vehicles (i.e., vehicles with larger footprints) will be subject to lower mpg targets than smaller vehicles. This is because, typically, smaller vehicles are more capable of achieving higher levels of fuel economy, mostly because they tend not to have to work as hard (and therefore to require as much energy) to perform their driving task. Although a manufacturer's fleet average standards could be estimated throughout the model year based on the projected production volume of its vehicle fleet (and are estimated as part of EPA's certification process), the standards with which the manufacturer must comply are determined by its final model year production figures. A manufacturer's calculation of its fleet average standards, as well as its fleets' average performance at the end

[25] 49 U.S.C. 32902(a)(3)(A).
[26] The product of vehicle wheelbase and average track width per 49 CFR 523.2.
[27] EPCA/EISA requires NHTSA and EPA to separate passenger cars into domestic and import passenger car fleets for CAFE compliance purposes (49 U.S.C. 32904(b)), whereas EPA combines all passenger cars into one fleet for CO_2 standards compliance.

of the model year, will thus be based on the production-weighted average target and performance of each model in its fleet.[28]

For passenger cars, consistent with prior rulemakings, NHTSA is defining final fuel economy targets as shown in Equation 1-1.

Equation 1-1: Passenger Car Fuel Economy Footprint Target Curve

$$TARGET_{FE} = \frac{1}{MIN\ [MAX\left(c \times FOOTPRINT + d,\ \frac{1}{a}\right), \frac{1}{b}]}$$

Where:

$TARGET_{FE}$ is the fuel economy target (in mpg) applicable to a specific vehicle model type with a unique footprint combination,

a is a minimum fuel economy target (in mpg),

b is a maximum fuel economy target (in mpg),

c is the slope (in gallons per mile per square foot, or gpm per square foot), of a line relating fuel consumption (the inverse of fuel economy) to footprint, and

d is an intercept (in gpm) of the same line.

Here, *MIN* and *MAX* are functions that take the minimum and maximum values, respectively, of the set of included values. For example, *MIN*[40, 35] = 35 and *MAX*(40, 25) = 40, such that *MIN*[*MAX*(40, 25), 35] = 35.

The resultant functional form is reflected in Chapter 1.4 below in graphs displaying the passenger car target function in each model year for each regulatory alternative.

For light trucks, also consistent with prior rulemakings, NHTSA is defining fuel economy targets as shown in Equation 1-2.

Equation 1-2: Light Truck Fuel Economy Footprint Target Curve

$$TARGET_{FE} = MAX\left(\frac{1}{MIN\left[MAX\left(c \times FOOTPRINT + d,\ \frac{1}{a}\right),\ \frac{1}{b}\right]}, \frac{1}{MIN\left[MAX\left(g \times FOOTPRINT + h,\ \frac{1}{e}\right),\ \frac{1}{f}\right]}\right)$$

Where:

$TARGET_{FE}$ is the fuel economy target (in mpg) applicable to a specific vehicle model type with a unique footprint combination,

a, *b*, *c*, and *d* are as for passenger cars, but taking values specific to light trucks,

e is a second minimum fuel economy target (in mpg),

f is a second maximum fuel economy target (in mpg),

g is the slope (in gpm per square foot) of a second line relating fuel consumption (the inverse of fuel economy) to footprint), and

h is an intercept (in gpm) of the same second line.

[28] As discussed in prior rulemakings, a manufacturer may have some vehicle models that exceed their target and some that are below their target. Compliance with a fleet average standard is determined by comparing the fleet average standard (based on the production-weighted average of the target levels for each model) with fleet average performance (based on the production-weighted average of the performance of each model).

As for the passenger car target function, the resultant functional form for light trucks is reflected in Chapter 1.4 below in graphs displaying the light truck target function in each model year for each regulatory alternative. Although the general model of the target function equation is the same for both passenger cars and light trucks, and each model year, the parameters of the function equation differ for cars and trucks.

For HDPUVs, NHTSA has previously set attribute-based standards, but used a work-based metric as the attribute rather than the footprint attribute used for passenger car and light truck standards. Work-based measures such as payload and towing capability are key among the parameters that characterize differences in the design of these vehicles, as well as differences in how the vehicles will be used. Buyers consider these utility-based attributes when purchasing a HDPUV. Since NHTSA has been regulating HDPUVs, these standards have been based on a “work factor” attribute that combines the vehicle’s payload and towing capabilities, with an added adjustment for 4-wheel drive vehicles.

Similar to the standards for passenger cars and light trucks, NHTSA (and EPA) have historically set HDPUV standards such that each manufacturer’s fleet average standard is based on production volume-weighting of target standards for all vehicles, that in turn are based on each vehicle’s work factor. These target standards are taken from a set of mathematical functions or curves. There is a target standard curve for compression ignition engine (CI) based HDPUVs and a target standard curve for spark ignition engine (SI) based HDPUVs. While NHTSA is not required by statute to set HDPUV standards that are attribute-based and that are described by a mathematical function, NHTSA continues to believe that doing so continues to be reasonable for this segment of vehicles, consistent with prior HDPUV standard-setting rulemakings. NHTSA is continuing to use the work-based attribute and to increase stringency gradually (which for HDPUVs means that standards appear to *decline*, as compared to passenger car and light truck standards where increasing stringency means that standards appear to *increase*), as discussed further below. NHTSA is defining HDPUV fuel efficiency targets as shown in Equation 1-3:

Equation 1-3: HDPUV Fuel Efficiency Work Factor Target Curve

$$\textit{Sub configuration Target Standard (gallons per 100 miles)}=[c \times (WF)]+d$$

Where:

c is the slope of the gasoline, CNG, Strong Hybrid, and PHEV work factor target curve in gal/100mile per WF

For diesel engines, BEVs, and FCVs, c will be replaced with e

d is the gasoline CNG, Strong Hybrid, and PHEV minimum fuel consumption work factor target curve value in gal/100mile

For diesel engines, BEVs, and FCVs, d will be replaced with f

$$WF = \text{Work Factor} = [0.75 \times (\text{Payload Capacity} + \text{Xwd})] + [0.25 \times \text{Towing Capacity}]$$

Where:

Xwd = 4wd adjustment = 500 lbs. if the vehicle group is equipped with 4wd and all-wheel drive (AWD), otherwise equals 0 lbs. for 2wd

Payload Capacity = GVWR (lbs.) – Curb Weight (lbs.) (for each vehicle group)

Towing Capacity = GCWR (lbs.) – GVWR (lbs.) (for each vehicle group)

To clarify, as has been the case since NHTSA began establishing attribute-based standards, no individual vehicle is required to meet the specific applicable fuel economy or fuel efficiency target, because compliance with CAFE and HDPUV standards is determined, per statute in the case of CAFE standards, based on corporate average performance. In this respect, CAFE and HDPUV standards are unlike, for example, Federal Motor Vehicle Safety Standards (FMVSS) and certain vehicle criteria pollutant emissions standards, where each vehicle must meet the requirements. Instead, CAFE and HDPUV standards apply to the average fuel economy or efficiency levels achieved by manufacturers' entire fleets of vehicles produced for sale in the United States. Safety standards apply on a vehicle-by-vehicle basis, such that every single vehicle produced for sale in the United States must, on its own, comply with applicable minimum FMVSS. When first mandating CAFE standards in the 1970s, Congress specified a more flexible averaging-based approach that allows some vehicles to "under-comply" (i.e., fall short of the overall flat standard, or fall short of their target under attribute-based standards) while others "over-comply" as long as a manufacturer's overall fleet is in compliance.

For passenger cars and light trucks, the required CAFE level applicable to a given fleet in a given model year is determined by calculating the production-weighted harmonic average of fuel economy targets applicable to specific vehicle model configurations in the fleet, as shown in Equation 1-4.

Equation 1-4: Calculation for Required CAFE Level

$$CAFE_{required} = \frac{\sum_i PRODUCTION_i}{\sum_i \frac{PRODUCTION_i}{TARGET_{FE,\,i}}}$$

Where:

$CAFE_{required}$ is the CAFE level that the fleet is required to achieve,

i refers to specific vehicle model/configurations in the fleet,

$PRODUCTION_i$ is the number of model configuration i produced for sale in the United States, and

$TARGET_{FE,\,i}$ is the fuel economy target (as defined above) for model configuration i.

For HDPUVs, the required fuel efficiency level applicable in a given model year is similarly determined by calculating the production-weighted average of subconfiguration targets applicable to specific vehicle model configurations in the fleet, as shown in Equation 1-5.[29]

Equation 1-5: Calculation for Required HDPUV Level

$$\text{Fleet Average Standard} = \frac{\sum [\textit{Subconfiguration Target Standard}_i \times \textit{Volume}_i]}{\sum [\textit{Volume}_i]}$$

Where:

$\textit{Subconfiguration Target Standard}_i$ = fuel consumption standard for each group of vehicles with the same payload, towing capacity, and drive configuration (gallons per 100 miles), and

$\textit{Volume}_i$ = production volume of each unique subconfiguration of a model type based upon payload, towing capacity, and drive configuration.

Chapter 1.2.2 describes the advantage of attribute-based standards, generally. Chapter 1.2.3 explains the specific decision to continue to use footprint, for passenger cars and light trucks, and work factor, for HDPUVs, as the attribute(s) over which to vary stringency. Chapter 1.2.4 discusses the mathematical functions for CAFE standards, and Chapter 1.2.5 discusses the mathematical functions for HDPUV standards.

1.2.2. Why Attribute-Based Standards, and What Are the Benefits?

As explained above, Congress expressly requires the passenger car and light truck CAFE standards to be attribute-based, and NHTSA continues to believe that it is reasonable to set attribute-based standards for

[29] 49 CFR 535.5(a)(2).

HDPUVs as well, given the many characteristics they share with light trucks (both in terms of technologies used and how they are manufactured). Under attribute-based standards, every vehicle model has a fuel economy or fuel efficiency target, the levels of which depend on the level of that vehicle's determining attribute. As discussed further below, in this final rule, NHTSA is retaining vehicle footprint as the attribute for passenger car and light truck CAFE standards, and to retain work factor as the attribute for model years 2030-2035 HDPUV standards. Again, the manufacturer's fleet average CAFE or HDPUV performance is calculated by the harmonic production-weighted average of those targets, as shown above in Equation 1-4 and Equation 1-5. This means that no vehicle is required to meet its target; instead, manufacturers are free to balance improvements however they deem best within (and in some cases, given credit transfers, at least partially across) their fleets.

While Congress expressly requires CAFE standards for passenger cars and light trucks to be specified as a mathematical function dependent on one or more attributes related to fuel economy, Congress has provided NHTSA the authority to select *which* attributes and mathematical functions, and Congress has also provided NHTSA broad authority in choosing how to regulate HDPUVs. Before Congress amended EPCA to require that CAFE standards be attribute-based and defined by a mathematical function, CAFE standards were instead specified as single mpg values (e.g., 27.5 mpg for passenger cars, 20.7 mpg for light trucks). Because these single-mpg standards were wholly independent of fleet composition, these requirements posed a significantly greater technical challenge for manufacturers producing more larger vehicles for the U.S. market than for manufacturers focused more on smaller vehicles, because smaller vehicles generally achieve greater fuel economy levels. Therefore, because the standards are fleet-average standards, these single-mpg standards presented an inherent incentive to shift production toward smaller vehicles rather than increasing the application of fuel-saving technologies across entire fleets, meaning that fuel economy benefits would be primarily available to purchasers of smaller vehicles, rather than broadly available to consumers with a more diverse range of vehicle preferences.

In setting attribute-based standards, NHTSA has sought to reflect the trade-off – i.e., the relationship – between the attribute and fuel economy/efficiency, consistent with the overarching purpose of EPCA/EISA to conserve energy. If the shape of the standards captures these trade-offs, every manufacturer is more likely to continue adding fuel-efficient technology across the distribution of the attribute within their fleet, instead of potentially changing the attribute – and other correlated attributes, including fuel economy/efficiency – as part of their compliance strategy. The shape of the standards is discussed in more detail in Chapter 1.4.

1.2.3. Attributes for Passenger Car, Light Truck, and HDPUV Standards

1.2.3.1. Footprint as the Attribute for Passenger Car and Light Truck CAFE Standards

49 U.S.C. 32902(b)(3)(A) states that the attribute used to set CAFE standards must be a "vehicle attribute related to fuel economy." While there are many vehicle attributes related to fuel economy, NHTSA has chosen to use vehicle footprint as the relevant attribute since model year 2011, the first year of CAFE standards set under EISA, and NHTSA is continuing this approach for the standards in this final rule.[30,31] Footprint has an observable correlation to fuel economy. There are several policy and technical reasons why NHTSA believes that footprint remains the most appropriate attribute on which to base CAFE standards for the vehicles covered by this rulemaking, even though some other vehicle attributes (notably, curb weight) are better correlated to fuel economy, and even though the 2021 NAS Report suggested adding another attribute.

First, the 2002 NAS Report described at length and quantified the potential safety problem with average fuel economy standards that specify a single numerical requirement for the entire industry,[32] identifying that smaller and lighter vehicles incentivized by those standards could be less safe for their occupants. Since that report, and because prior litigation has concerned the possible safety effects associated with CAFE standards, NHTSA has sought to set CAFE standards with an eye toward these possible effects. Because

[30] We note that EPA has also set its CO_2 standards for light-duty vehicles using footprint as the attribute since model year 2012.
[31] A vehicle's footprint is defined as the vehicle's track width multiplied by the vehicle's wheelbase and rounded to the nearest 1/10 squared foot, per 49 CFR 523.2.
[32] Transportation Research Board and National Research Council. 2002. Effectiveness and Impact of Corporate Average Fuel Economy (CAFE) Standards. *The National Academies Press*: Washington, D.C. pp. 5, 12. Available at: https://nap.nationalacademies.org/catalog/10172/effectiveness-and-impact-of-corporate-average-fuel-economy-cafe-standards. (Accessed: Feb 7, 2024) (hereafter, "2002 NAS Report").

vehicle size is correlated with vehicle safety at least for the occupants of the vehicles, and because CAFE standards can affect vehicle size when manufacturers are considering how to improve the fuel economy of their vehicles, NHTSA believes it is important to choose an attribute correlated with vehicle size (mass or some dimensional measure).

As discussed in NHTSA's model year 2011 CAFE final rule, when first electing to adopt footprint-based standards for both passenger cars and light trucks, NHTSA carefully considered other alternatives, including vehicle mass and "shadow" (overall width multiplied by overall length). Vehicle mass is strongly correlated with fuel economy: on a per-mile basis, a vehicle with more mass takes more energy to move than a vehicle with less mass. Mass and crush space are both important safety considerations, and mass *disparity,* in particular, can affect crash outcomes for all parties. Mass is also quite easy to manipulate artificially (i.e., changing the attribute(s) to achieve a more favorable target). Without much difficulty, a manufacturer could add enough mass to a vehicle to decrease its applicable fuel economy target by a significant amount – even infotainment systems add weight through components, wiring, etc. Mass-based standards can also discourage manufacturers from applying mass-efficient materials and designs, because their standards would become more stringent as mass is reduced. A mass-based attribute would provide the wrong incentive given that EPCA's objective is energy conservation.

In comparison, footprint is also correlated with fuel economy but not as strongly as mass. Footprint has a positive correlation with frontal surface area, and front surface area has a negative correlation with aerodynamic drag, and therefore with fuel economy. However, the relationship is less deterministic than mass. Footprint is also less directly associated with vehicle occupant safety, as discussed in Chapter 7. As compared to mass, NHTSA continues to believe that footprint is much less susceptible to gaming, because while there is some potential to adjust track width, wheelbase is more difficult and expensive to change, at least outside a planned vehicle redesign – it cannot easily be adjusted year to year, unlike mass. Among other things, changes in footprint can affect vehicle dynamics, for example, requiring reevaluation of compliance with certain FMVSS and safety system performance. This is not to say that a footprint-based standard eliminates manipulation, or that a footprint-based system eliminates the possibility that manufacturers will change vehicles in ways that compromise safety.

Based on the data present in the EPA Trends report,[33] see Table 1-2 below, we see that vehicle footprints, within vehicle types, have been stable on a sales weighted basis since model year 2012, with the sedan/ wagon category seeing the largest increase of footprint at a 3.4% increase, or about a 2 square foot increase. A 1.5 square foot increase would equate to about a 2-inch increase in the track width of a model year 2022 Toyota Corolla.[34] Furthermore, despite the slight increases in footprint, many vehicle categories show a reduction in vehicle mass, on a sales-weighted average, including a 164 lbs. decrease in weight for pickups. However, when the sales-weighted average for both of these characteristics, footprint and weight, are taken in aggregate, an overall 5.4% increase in footprint and 325 lbs. increase in weight is seen over the time period.

The disconnect between *vehicle-class* level characteristics and the *aggregate* fleet characteristics is directly traceable to the change in fleet share. The increase in sales-weighted average footprint, as well as weight, is directly caused by the nearly 28.4% reduction in fleet share for the smaller footprint sedans/wagons, in exchange for the 29.5% increase in fleet shares for larger-footprint truck sport utility vehicles (SUVs) and pickups.

Table 1-2: EPA Trends Report Data for 2012 and 2022 Fleet Share, Footprint and Weight Comparison

	Fleet Share (%)			Footprint (ft^2)			Weight (lbs.)		
	2012	**2022**	**Delta**	**2012**	**2022**	**%Delta**	**2012**	**2022**	**Lbs. Delta**
All	100%	100%	0.00%	49	52	5.4%	3979	4303	325

[33] 2023 EPA Trends Report.
[34] The model year 2022 Corolla has a wheelbase of about 106 inches, adding 2 inches to the track width would add approximatly 212 square inches or 1.47 square feet to the footprint of the vehicle. See the Baseline Fleet Input File for data on the 2022 Corolla wheelbase.

Sedan/ Wagon	55.0%	26.5%	-28.4%	45	47	3.4%	3452	3597	145
Minivan/Van	4.9%	2.9%	-2.0%	55	56	2.1%	4442	4559	117
Car SUV	9.4%	10.4%	1.0%	47	48	1.6%	3915	3890	-25
Truck SUV	20.6%	43.8%	23.2%	50	50	0.9%	4640	4488	-151
Pickup	10.1%	16.4%	6.3%	64	65	0.5%	5335	5171	-164

Reviewing these trends shows us that the aggregate increase in footprint size is primarily driven by fleet share changes and not large increases in vehicle class footprint sizes. This evidence leads us to conclude the use of footprint as an attribute for passenger car and light truck CAFE standards does not lead to manufacturers significantly altering the size of their vehicles, within vehicle classes. This also supports our decision not to adjust the footprint functions, discussed below. The major shift in vehicle fleet share in this analysis is not considered a result of the use of the footprint attribute or of the shape of the standards curves but is likely a function of the difference in stringency between the passenger car and light truck fleets and will be considered when setting stringencies.

The question has also arisen periodically of whether NHTSA should instead consider multi-attribute standards for CAFE, such as those that also depend on mass, torque, power, towing capability, and/or off-road capability. To date, every time NHTSA has considered options for which attribute(s) to select, the agency has concluded that a properly-designed footprint-based approach provides the best means of achieving the basic policy goals[35] involved in applying an attribute-based standard. At the same time, footprint-based standards can be structured in a way that furthers the energy and environmental policy goals of EPCA/EISA by not creating inappropriate incentives to increase vehicle size in ways that could increase fuel consumption.

In the 2021 NAS Report, the committee recommended that if Congress does not act to remove the prohibition at 49 U.S.C. 32902(h) on considering the fuel economy of dedicated AFVs (like BEVs) in determining maximum feasible CAFE standards, then the Secretary (or agency) should consider accounting for the fuel economy benefits of ZEVs by "setting the standard as a function of a second attribute in addition to footprint – for example, the expected market share of ZEVs in the total U.S. fleet of new light-duty vehicles – such that the standards increase as the share of ZEVs in the total U.S. fleet increases."[36] While NHTSA considered this recommendation carefully and sought comment on an approach to implementing it, NHTSA ultimately agreed with many commenters that including electrification as an attribute on which to base fuel economy standards may be inconsistent with our current legal authority.

1.2.3.2. Work Factor as the Attribute for HDPUV Standards

NHTSA and EPA originally considered Gross Vehicle Weight Rating (GVWR) and Gross Combined Weight Rating (GCWR) as possible attributes for setting fuel efficiency standards for the HDPUV fleet. However, concerns over gaming the mass of the vehicles exist, similar to concerns expressed for using mass or weight as the attribute for passenger cars and light trucks. Additionally, under GVWR- or GCWR-based standards, allowing worse fuel efficiency from vehicles with higher curb weight would tend to penalize light-weighted vehicles with comparable payload capabilities by making them meet more stringent standards than they would have had to meet without the weight reduction. The agencies concluded that using payload and towing capacities as the work-based attributes would avoid the gaming risk and also avoid penalizing light-weighting. These attributes were combined into a "work factor," with an additional fixed adjustment for four-wheel drive vehicles to account for the fact that 4wd, critical to enabling many off-road heavy-duty work applications, adds roughly 500 lbs. to the vehicle weight.

[35] Increasing the likelihood of improved fuel economy across the entire fleet of vehicles; by reducing disparities between manufacturers' compliance burdens; and by reducing incentives for manufacturers to respond to standards by reducing vehicle size in ways that could compromise occupant safety.
[36] National Academies of Sciences, Engineering, and Medicine. 2021. Assessment of Technologies for Improving Fuel Economy of Light-Duty Vehicles – 2025-2035. *The National Academies Press*: Washington, D.C. p. 5. Available at: https://www.nationalacademies.org/our-work/assessment-of-technologies-for-improving-fuel-economy-of-light-duty-vehicles-phase-3. (Accessed Feb. 7, 2024) (hereinafter, "2021 NAS Report"). Summary Recommendation 5, p. 368.

Towing does not directly factor into test weight, as nothing is towed during the test. Thus, only the higher curb weight caused by heavier truck components would affect measured test results. However, towing capacity can still be a significant factor because heavy-duty pickup truck towing capacities can be quite large, with a correspondingly large effect on design, and thus on possible fuel efficiency levels.

NHTSA and EPA also noted that, from a HDPUV purchaser perspective, payload and towing capability typically play a greater role than physical dimensions (as footprint represents) in influencing purchaser decisions on which heavy-duty vehicle to buy.

NHTSA continues to believe that "work factor" remains a reasonable attribute on which to base HDPUV fuel efficiency standards. Such standards are meant to be relatively consistent from a stringency perspective. Vehicles across the entire range of the HDPUV segment have their respective fuel consumption target values, and therefore all HDPUVs will be affected by the standard. With an attribute-based standards approach, there should be no significant effect on the relative distribution of vehicles with differing capabilities in the fleet, which means that buyers should still be able to purchase the vehicle that meets their needs.

1.2.4. Choosing the Mathematical Function to Specify Footprint-Based Standards for Passenger Cars and Light Trucks

In requiring NHTSA to "prescribe by regulation separate average fuel economy standards for passenger and non-passenger automobiles based on 1 or more vehicle attributes related to fuel economy and express each standard in the form of a mathematical function," EPCA/EISA provides discretion regarding not only the selection of the attribute(s), but also regarding the nature of the function. Having decided to establish passenger car and light truck standards that continue to be based on vehicle footprint as the attribute "related to fuel economy," NHTSA still must choose the mathematical functions to represent the relationship between footprint and fuel economy.

The relationship between fuel economy and footprint, though directionally clear (i.e., fuel economy tends to decrease with increasing footprint), is theoretically vague, and quantitatively uncertain – not so precise as to necessarily yield only a single possible curve. The decision of how to specify this mathematical function therefore reflects some amount of judgment. The function can be specified with a view toward achieving different levels of energy conservation (which may include both energy security and environmental goals), encouraging different levels of application of fuel-saving technologies, avoiding any adverse effects on overall highway safety, reducing disparities of distributing compliance burdens (and thus fuel economy improvements) more equally across manufacturers, and preserving consumer choice amongst different types and sizes of vehicles, among other aims. The following are among the specific technical concerns and resultant policy tradeoffs that NHTSA has previously considered in selecting the details of specific past and future curve shapes:

- Steeper footprint-based standards may create incentives to upsize vehicles, potentially oversupplying vehicles of certain footprints beyond what the market would demand, and thus increasing the possibility that fleetwide (or total) fuel savings benefits will be forfeited artificially.
- Flatter standards (curves) increase the risk that standards cannot be met by larger vehicles without significant cost, making them unaffordable or removing them from certain markets, reducing the supply of options for consumers who may need the utility of a larger vehicle.
- Given the same industry-wide average required fuel economy standard, flatter standards tend to place greater compliance burdens on full-line manufacturers, although this is not necessarily true if the vehicles are ZEVs.
- If cutpoints (i.e., locations of rapid change in slope, as with piecewise-linear functions) are adopted, given the same industry-wide average required fuel economy, moving small-vehicle cutpoints to the left (i.e., up, in terms of fuel economy) discourages the introduction of small vehicles, and reduces the incentive to downsize small vehicles.
- If cutpoints are adopted, given the same industry-wide average required fuel economy, moving large-vehicle cutpoints to the right (i.e., down, in terms of fuel economy) encourages the introduction of larger vehicles – especially large pickups – and extends the size range over which downsizing is discouraged in ways that could compromise overall highway safety.

NHTSA is retaining the same curve shapes for passenger car and light truck standards in in this final rule that NHTSA has used over the past several rulemakings – that is, at this time NHTSA is not changing the shape of the existing footprint curves. The history of how the existing footprint curves were developed, and the agency's exploration of alternative approaches, is well documented in Chapter 1 of the 2022 TSD,[37] and we refer readers there who wish to review that history. NHTSA carefully considered the existing curve shapes in light of ongoing trends in the fleet,[38] and determined, as in the 2022 TSD, that changing our approach to standard *stringency* made more sense for CAFE standards than changing the *curve shapes* at this point. As explained in the 2022 TSD and discussed in Chapter 3 of the 2023 EPA Trends Report, for the most part, vehicle manufacturers have continued over the past several years to reduce their offerings of smaller footprint vehicles, such as sedans and wagons, and increase their sales of larger footprint vehicles such as light truck crossovers and sport utility vehicles (SUVs).

That said, NHTSA is aware that EPA recently issued a final rule changing the shapes of its CO_2 standards curves for passenger cars and light-duty trucks, as compared to its prior set of standards.[39] EPA explained that it chose to make the slopes of both curves, especially the car curves, flatter than those of prior rulemakings, stating that, "When emissions reducing technology is applied, such as advanced ICE, or HEV or PHEV or BEV electrification technologies, the relationship between increased footprint and tailpipe emissions is reduced. From a physics perspective, a positive footprint slope for ICE vehicles makes sense because as a vehicle's size increases, its mass, road loads, and required power (and corresponding vehicle-based CO_2 emissions) will increase accordingly [and its fuel economy will correspondingly decrease accordingly]. Moreover, as the emissions control technology becomes increasingly more effective, the relationship between tailpipe emissions and footprint decreases proportionally; in the limiting case of vehicles with 0 g/mile tailpipe emissions such as BEVs, there is no relationship at all between tailpipe emissions and footprint."[40]

Since the Supreme Court's decision in Massachusetts v. EPA, NHTSA and EPA have employed equivalent footprint-based target curves for passenger cars and light trucks. Now, NHTSA cannot reasonably promulgate target curves that are flatter like EPA's new curves based on EPA's rationale, for two main reasons. First, EPA altered their curves based on considering the effects of BEVs in the fleet. Given that the target curves *are* the CAFE standards, and 49 U.S.C. 32902(h) prohibits consideration of BEVs in determining maximum feasible CAFE standards, NHTSA does not believe that the law permits us to base target curve shapes on BEV penetration rates, even if NHTSA recognizes that BEV penetration rates are continuing to increase. Second, even if NHTSA did consider BEVs in developing target curve shapes, NHTSA could not consider them the same way as EPA does. BEV compliance values in the CAFE program are determined, per statute, using DOE's Petroleum Equivalency Factor, and the calculated equivalent fuel economies appear to still vary with vehicle footprint so that, in general, larger vehicles have lower calculated equivalent fuel economies. They are not the fuel-economy-equivalent of 0 g/mi, which would be infinite fuel economy. NHTSA therefore cannot adopt EPA's rationale that curve slopes should become flatter in response to increasing numbers of BEVs because our statutory requirements differ from EPA's.

EPA also proposed that the "truck curve [for CO_2 standards] be based on the car curve (to represent the base utility across all vehicles for carrying people and their light cargo), but with the additional allowance of increased utility that distinguishes these vehicles used for more work-like activity."[41] To account for tow rating, "EPA proposes a simple offset for the truck curve, compared to the car curve, that increases with footprint," and "The offsets for AWD and utility were then scaled as a function of the nominal fleet-wide BEV penetrations anticipated to be achieved under the final stringency levels."[42] EPA additionally proposed to gradually reduce the upper (larger footprint) cutpoint for trucks, in response to concern that the existing cutpoint might create a compliance incentive to upsize.[43]

[37] U.S. Department of Transportation. 2022. Technical Support Document: Final Rulemaking for Model Years 2024-2026 Light-Duty Vehicle Corporate Average Fuel Economy Standards. Final report. National Highway Traffic Safety Administration. Washington D.C. Available at: https://www.nhtsa.gov/sites/nhtsa.gov/files/2022-04/Final-TSD_CAFE-MY-2024-2026.pdf. (Accessed: Feb 7, 2024).
[38] See trends discussion in Chapter 1.2.3.1.
[39] 89 FR 27842 (April 18, 2024)
[40] 89 FR 27842, 27904 (April 18, 2024)
[41] *Id*. at 29235.
[42] *Id*.
[43] *Id*. at 29236.

Again, NHTSA does not interpret 49 U.S.C. 32902(h) as permitting the agency to base target curves on anticipated BEV penetrations; that said, NHTSA is also aware of the need for the light truck curve to reflect the work performed by those "more work-like" vehicles, which must be balanced against the risk of encouraging upsizing. To address this in the CAFE program, NHTSA is retaining the existing light truck curve, which was originally designed to reflect those work needs.

For these reasons, NHTSA cannot justify making similarly-shaped curves for passenger cars and light trucks under our current authority, and the agency did not consider adopting such curves in this final rule. NHTSA may nonetheless explore reasonable and appropriate changes to the existing curve shapes in a future action.

1.2.5. Choosing the Mathematical Function to Specify Work-Factor-Based Standards for HDPUVs

As discussed, NHTSA is not statutorily required to set attribute-based standards defined by a mathematical function for HDPUVs, but previously concluded that doing so was reasonable and appropriate given the similarities of the HDPUV fleet to the light truck fleet, and NHTSA continues to believe that is the case. NHTSA previously chose to set HDPUV standards based on a "work factor" attribute, which combines elements of both payload and towing capabilities. These attributes, like footprint for passenger cars and light trucks, relate to fuel consumption in a way that is directionally clear – more payload and/or more towing equals more fuel consumed, all else equal – but also like footprint, there are many different possible curves that could theoretically represent that relationship. As in the Phase 2 rule, NHTSA is retaining the approach to curve fitting set forth in the Phase 1 rule.[44] The basic work factor equation is shown in Chapter 1.2.3, and NHTSA is retaining separate target curves for gasoline-fueled (and any other Otto-cycle) vehicles and diesel-fueled (and any other Diesel-cycle) vehicles. The targets will be used to determine the production-weighted average standards that apply to the combined diesel and gasoline fleet of HDPUVs produced by a manufacturer in each model year. The targets were based on a set of vehicle, engine, and transmission technologies (TRANS) assessed by NHTSA and EPA to be feasible and appropriate for HDPUVs in the 2014-2018 timeframe, and while it is certainly appropriate for the stringency of the standards to increase over time, there does not appear to be a reason to re-evaluate the shape of the target curves themselves. As discussed further in Chapter 2.2, HDPUVs have significantly longer redesign schedules as compared to passenger cars and light trucks, and technology changes tend to percolate through the HDPUV fleet relatively more slowly, which makes it less likely that the shape of the target curves would need to change in response. For example, with the exception of a few low-volume BEVs in this segment,[45] there are no other electrified technologies in the current baseline fleet.[46]

The NHTSA fuel consumption target curves and the EPA GHG target curve have considerable overlap during common years. In the Phase 2 rule, NHTSA target curves were established using the direct relationship between fuel consumption and CO_2 using conversion factors of 8,887 g CO_2/gallon for gasoline, and 10,180 g CO_2/gallon for diesel. We maintained the same approach for this rule, but due to statutory lead time constraints, NHTSA's year over year stringency increases delayed in comparison to what EPA established for its recently-promulgated CO_2 target curves. NHTSA's HDPUV standards aim to trail the EPA stringencies in the early years and 'catch up' to the EPA standards by model year 2035.

1.3. What Does the CAFE Model Need to Conduct This Analysis?

To conduct the analysis described above, the CAFE Model needs a variety of inputs. At a high level, the model needs the following: regulatory alternatives (see Chapter 1.4), an analysis fleet (see Chapter 2.2), information to simulate compliance with the State ZEV programs (see Chapter 5.1), technology effectiveness values (see Chapter 2.3 and Chapter 3), technology cost information (see Chapter 3), economic assumptions (see Chapter 4 for macroeconomic assumptions and Chapters 5, 6, and 7 for all others), and estimates about

[44] *See* 76 FR 57162-64 (Sep. 15, 2011) for a complete discussion.
[45] Ford Lightning Platinum, and Extended Range
[46] Electrified technologies in this context means micro-hybrids, mild hybrids, strong hybrids, battery electric and plug-in hybrids as well as fuel cell vehicles.

environmental (see Chapter 5) and safety (see Chapter 7) effects. Chapter 2 discusses the required inputs in more detail.

1.4. What Are the Regulatory Alternatives Under Consideration in This Final Rule?

Agencies typically consider regulatory alternatives in rulemaking analyses as a way of evaluating the comparative effects of different potential ways of accomplishing their desired goal, which in this case is the statutory mandate to set maximum feasible standards. NEPA requires agencies to compare the potential environmental impacts of their regulatory actions to those of a reasonable range of alternatives.[47] E.O. 12866 and E.O. 13563, as well as Office of Management and Budget (OMB) Circular A-4, also encourage agencies to evaluate regulatory alternatives in their rulemaking analyses.

Alternatives analysis begins with a “No-Action” Alternative, typically described as what would occur in the absence of any regulatory action by the agency – in other words, the reference baseline. OMB Circular A-4 states that “the choice of an appropriate reference baseline may require consideration of a wide range of potential factors, including:

- evolution of the markets;
- changes in regulations promulgated by the agency or other government entities;
- other external factors affecting expected benefits and costs;
- the degree of compliance by regulated entities with other regulations; and
- the scale and number of entities or individuals that will be subject to, or experience the benefits or costs of, the regulation.”[48]

For passenger cars and light trucks, this final rule includes a No-Action Alternative and five “action alternatives;” for HDPUVs, the final rule includes a No-Action Alternative and four action alternatives. The final standards may, in places, be referred to as the “Preferred Alternative(s),” which is NEPA parlance, but NHTSA intends “final standards” and “Preferred Alternative(s)” to be used interchangeably for purposes of this document.

Regulations regarding implementation of NEPA require agencies to “evaluate reasonable alternatives to the final action and the alternatives in comparative form” based on the affected environment and environmental consequences.[49] This does not amount to a requirement that agencies evaluate the widest conceivable spectrum of alternatives. Rather, the range(s) of alternatives must be reasonable and consistent with the purpose and need of the action(s).

The different regulatory alternatives for passenger cars and light trucks are defined in terms of percent-changes in CAFE stringency from year to year. Readers should recognize that those year-over-year changes in stringency are *not* measured in terms of mile per gallon differences (as in, 1 percent more stringent than 30 miles per gallon (MPG) in one year equals 30.3 MPG in the following year), but rather in terms of shifts in the *footprint functions* that form the basis for the *actual* CAFE standards (as in, on a gallon per mile basis, the CAFE standards change by a given percentage from one model year to the next).

In a departure from recent CAFE rulemaking trends, for this final rule we have applied individual, different rates of increase to the passenger car and the light truck fleets in different model years. Rather than have both fleets increase their respective standards at the same rate, passenger car standards will increase at a steady rate year over year, while light truck standards will not increase for few years before beginning to rise again at the passenger car rate. Several action alternatives evaluated for this final rule have a passenger car fleet rates-of-increase of fuel economy that are different from the rates-of-increase of fuel economy for the light truck fleet, while one action alternative has the same rate of increase for passenger cars and light trucks

[47] 40 CFR 1502.14.
[48] See Office of Management and Budget. 2023. Circular A-4. General Issues, 4. Developing an Analytic Baseline. Available at: https://www.whitehouse.gov/wp-content/uploads/2023/11/CircularA-4.pdf. (Accessed: Apr. 4, 2024).
[49] 40 CFR 1502.14.

for all model years. NHTSA has discretion, by law, to set CAFE standards that increase at different rates for cars and trucks, because NHTSA must set maximum feasible CAFE standards separately for cars and trucks.

For HDPUVs, the different regulatory alternatives are also defined in terms of percent-increases in stringency from year to year, but in terms of fuel consumption reductions rather than fuel economy increases, so that increasing stringency appears to result in standards going *down* (representing a direct reduction in fuel consumed) over time rather than *up*. Also, unlike for the passenger car and light truck standards, because HDPUV standards are in fuel consumption space, year-over-year percent changes do actually represent gallon/mile differences across the work-factor range. Under each action alternative, the stringency changes are the same, or a slightly different percentage in the case of the preferred alternative, rates in each model year in the rulemaking time frame. One action alternative is less stringent than the Preferred Alternative for HDPUVs, and two action alternatives are more stringent.[50]

Table 1-3: Regulatory Alternatives Under Consideration for MYs 2027-2031 Passenger Cars and Light Trucks

Name of Alternative	Passenger Car Stringency Increases, Year-Over-Year	Light Truck Stringency Increases, Year-Over-Year
No-Action Alternative	n/a	n/a
Alternative PC1LT3	1%	3%
Alternative PC2LT002 (Preferred Alternative)	2%	0% MYs 2027-28 2% MYs 2029-32
Alternative PC2LT4 (Preferred Alternative)	2%	4%
Alternative PC3LT5	3%	5%
Alternative PC6LT8	6%	8%

Table 1-4: Regulatory Alternatives Under Consideration for MYs 2030-2035 HDPUVs

Name of Alternative	HDPUV Stringency Increases, Year-Over-Year
No-Action Alternative	n/a
Alternative HDPUV4	4%
Alternative HDPUV108 (Preferred Alternative)	10% MYs 2030-32 8% MYs 2033-35
Alternative HDPUV10	10%
Alternative HDPUV14	14%

A variety of factors will be at play simultaneously as manufacturers seek to comply with the eventual standards that NHTSA promulgates. NHTSA, EPA, and CARB will all likely be regulating simultaneously; manufacturers will be responding to those regulations as well as to anticipated shifts in market demand during the rulemaking time frame (both due to cost/price changes for different types of vehicles over time, fuel price changes, and the recently-passed tax credits for BEVs and PHEVs). Many costs and benefits that will accrue as a result of manufacturer actions during the rulemaking time frame will be occurring for reasons other than CAFE standards, and NHTSA believes it is important to try to reflect as many of those factors as possible in order to present a more accurate picture of the effects of different potential CAFE and HDPUV standards to decision-makers and to the public.

[50] The PC, LT, and HDPUV target curve function coefficients are defined above in Equations 1-1, 1-2, and 1-3, respectively. See Chapter 1.2.1 for a complete discussion about the footprint and work factor curve functions and how they are calculated.

The following sections define each regulatory alternative, including the No-Action Alternative, for each program, and explain their derivation.

1.4.1. Reference baseline/No-Action Alternative

As with the 2022 final rule, our No-Action Alternative is nuanced. In this analysis, the No-Action alternative assumes:

- The existing (through model year 2026) national CAFE and GHG standards are met, and that the CAFE and GHG standards for model year 2026 finalized in 2022 continue in perpetuity.[51]
- Manufacturers who committed to the California Framework Agreements met their contractual obligations for model year 2022.
- The HDPUV model year 2027 standards finalized in the NHTSA/EPA Phase 2 program continue in perpetuity.
- Manufacturers will take action to comply with and assume implementation of the ZEV/Advanced Clean Cars I(ACC I)/Advanced Clean Trucks (ACT) programs that California and other states intend to implement through 2035.
- Manufacturers will voluntarily deploy electric vehicles consistent with ACC II program, regardless of whether it becomes legally binding.[52]
- Manufacturers will make production decisions in response to estimated market demand for fuel economy or fuel efficiency, considering estimated fuel prices, estimated product development cadence, the estimated availability, applicability, cost, and effectiveness of fuel-saving technologies, and available tax credits.
- This No-Action Alternative also includes NHTSA's estimates of ways that manufacturers could take advantage of recently passed tax credits for battery-based vehicle technologies[53]

NHTSA continues to believe that to properly estimate fuel economies/efficiencies (and achieved CO_2 emissions) in the No-Action Alternative, it is necessary to simulate all of these legal requirements and other influences affecting automakers and vehicle design simultaneously. Consequently, the CAFE Model evaluates each requirement in each model year, for each manufacturer/fleet. Differences among fleets and compliance provisions often create over-compliance in one program, even if a manufacturer is able to exactly comply (or under-comply) in the other program. This is similar to how manufacturers approach the question of concurrent compliance in the real world – when faced with multiple regulatory programs, the most cost-effective path may be to focus efforts on meeting one or two sets of requirements, even if that results in "more effort" than would be necessary for another set of requirements, in order to ensure that all regulatory obligations are met. We elaborate on those model capabilities below. Generally speaking, the model treats each manufacturer as applying the following logic when making technology decisions, both for simulating passenger car and light truck compliance, and HDPUV compliance, with a given regulatory alternative:

1. What do I need to carry over from last year?
2. What should I apply more widely in order to continue sharing (of, e.g., engines) across different vehicle models?
3. What new BEVs do I need to build in order to satisfy the various state ZEV programs and voluntary deployment of electric vehicles consistent with ACC II?
4. What further technology, if any, could I apply that would enable buyers to recoup additional costs within 30 months after buying new vehicles for both light-duty and HDPUV?
5. What additional technology, if any, should I apply to respond to potential new CAFE and CO_2 standards for passenger cars and light trucks, or HDPUV standards?

[51] NHTSA recognizes EPA may publish their 27+ standards before this final rule is published, however, EPA's 27+ standards were not included in the reference baseline analysis, as the agencies developed their respective 27+ standards jointly.
[52] California, Colorado, Connecticut, Delaware, Maine, Maryland, Massachusetts, Minnesota, Nevada, New Jersey, New Mexico, New York, Oregon, Rhode Island, Vermont, Virginia, and Washington have all adopted some combination of the ACC and/or ACT standards.
[53] The AMPC and CVC provide tax credits for light-duty and HDPUV PHEVs, BEVS, and FCEVs. Chapter 2.2 below discusses, in detail, how NHTSA has modeled these tax credits.

Additionally, within the context of 4 and 5, the CAFE Model may consider, as appropriate, the applicability of recently-passed tax credits for battery-based vehicle technologies, such as PHEVs, which improve the attractiveness of those technologies to consumers and thus the model's likelihood of choosing them as part of a compliance solution. The CAFE Model simulates all of these simultaneously. As mentioned above, this means that when manufacturers make production decisions in response to actions or influences other than CAFE or HDPUV standards, those costs and benefits are not attributable to possible future CAFE or HDPUV standards. One consequence, in turn, is that the effects of the final rule appear less cost-beneficial than they would otherwise, but NHTSA believes this is appropriate in order to give the decision-maker the clearest possible understanding of the effects of the decision being made, as opposed to the effects of the many things discussed above, that will be occurring simultaneously and would have happened otherwise.

Existing NHTSA standards during the rulemaking time frame are modeled as follows:

To account for the existing model year 2026 passenger car and light truck standards, the No-Action Alternative includes the following coefficients defining those standards, which (for purposes of this analysis) are assumed to persist without change in subsequent model years:

Table 1-5: Passenger Car CAFE Target Function Coefficients for No-Action Alternative[54]

	2027	2028	2029	2030	2031	2032 (augural)
a (mpg)	66.95	66.95	66.95	66.95	66.95	66.95
b (mpg)	50.09	50.09	50.09	50.09	50.09	50.09
c (gpm per s.f.)	0.00033512	0.00033512	0.00033512	0.00033512	0.00033512	0.00033512
d (gpm)	0.00119613	0.00119613	0.00119613	0.00119613	0.00119613	0.00119613

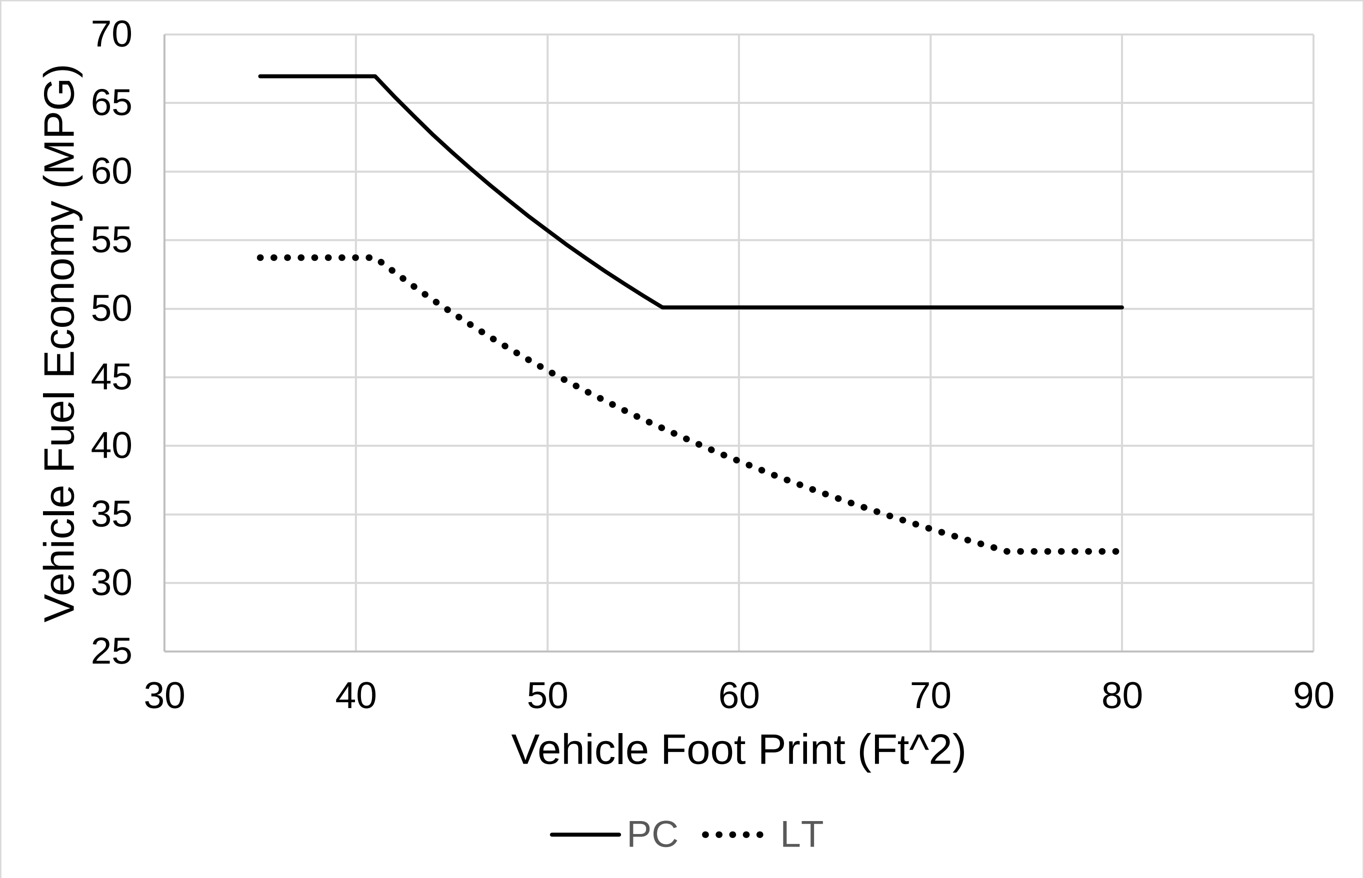
Table 1-6: Light Truck CAFE Target Function Coefficients for No-Action Alternative[55]

	2027	2028	2029	2030	2031	2032 (augural)
a (mpg)	53.73	53.73	53.73	53.73	53.73	53.73
b (mpg)	32.30	32.30	32.30	32.30	32.30	32.30
c (gpm per s.f.)	0.00037418	0.00037418	0.00037418	0.00037418	0.00037418	0.00037418
d (gpm)	0.00327158	0.00327158	0.00327158	0.00327158	0.00327158	0.00327158

These coefficients are used to create the following graphic below, where the x-axis represents vehicle footprint and the y-axis represents fuel economy, showing that in "CAFE space," targets are higher in fuel economy for smaller footprint vehicles and lower for larger footprint vehicles:

[54] The Function Coefficients 'a','b','c', and 'd' are defined in Equation 1-1 of Chapter 1.2.1.
[55] The Function Coefficients 'a','b','c', and 'd' are defined in Equation 1-1 of Chapter 1.2.1.

Figure 1-3: No-Action Alternative, Passenger Car and Light Truck Fuel Economy, Target Curves



Note: There is no model year associated with the No-Action Alternative in this figure because the same curve would apply in all relevant MYs.

Additionally, EPCA, as amended by EISA, requires that any manufacturer's domestically-manufactured passenger car fleet must meet the greater of either 27.5 mpg on average, or 92 percent of the average fuel economy projected by the Secretary for the combined domestic and non-domestic passenger automobile fleets manufactured for sale in the United States by all manufacturers in the model year. NHTSA retains the 1.9 percent offset to the minimum domestic passenger car standard (MDPCS), first used in the 2020 final rule, to account for recent projection errors as part of estimating the total passenger car fleet fuel economy.[56] The projection shall be published in the Federal Register when the standard for that model year is promulgated in accordance with 49 U.S.C. 32902(b).[57,58] For purposes of the No-Action Alternative, the MDPCS is as it was established in the 2022 final rule for model year 2026, as shown in Table 1-7 below:

Table 1-7: No-Action Alternative – Minimum Domestic Passenger Car Standard (MPG)

2027	2028	2029	2030	2031	2032 (augural)
53.5	53.5	53.5	53.5	53.5	53.5

To account for the existing HDPUV standards finalized in the Phase 2 rule, the No-Action Alternative for HDPUVs includes the following coefficients defining those standards, which (for purposes of this analysis) are assumed to persist without change in subsequent model years. The four-wheel drive coefficient is maintained

[56] Preamble Section V.A.2 (titled "Separate Standards for Passenger Cars, Light Trucks, and Heavy-Duty Pickups and Vans, and Minimum Standards for Domestic Passenger Cars") discusses the basis for the offset.
[57] 49 U.S.C. 32902(b)(4).
[58] The offset will be applied to the final regulation numbers, but was not used in this analysis. The values for the MDPCS for the final action alternatives are nonadjusted values.

at 500 (coefficient 'a') and the weighting multiplier coefficient is maintained at 0.75 (coefficient 'b'). The CI and SI coefficients are in the tables below:

Table 1-8: HDPUV CI Vehicle Fuel Efficiency Target Function Coefficients for No-Action Alternative[59]

	2030	2031	2032	2033	2034	2035
e (gal/100 miles per WF)	0.00034180	0.00034180	0.00034180	0.00034180	0.00034180	0.00034180
f (gal/100 miles per WF)	2.633	2.633	2.633	2.633	2.633	2.633

Table 1-9: HDPUV SI Vehicle Fuel Efficiency Target Function Coefficients for No-Action Alternatives[60]

	2030	2031	2032	2033	2034	2035
c (gal/100 miles per WF)	0.00041520	0.00041520	0.00041520	0.00041520	0.00041520	0.00041520
d (gal/100 miles per WF)	3.196	3.196	3.196	3.196	3.196	3.196

These equations are represented graphically below:

[59] In the CAFE Model, these are Linear work-factor-based function where coefficients e and f are for diesels, BEVs and FCEVs. See Equation 1-3 in Chapter 1.2.1.

[60] In the CAFE Model, these are Linear work-factor-based function where coefficients c and d are for gasoline, CNG, strong hybrid vehicles and PHEVs. See Equation 1-3 in Chapter 1.2.1.

Figure 1-4: No-Action Alternative, HDPUV – CI Vehicles, Target Curves

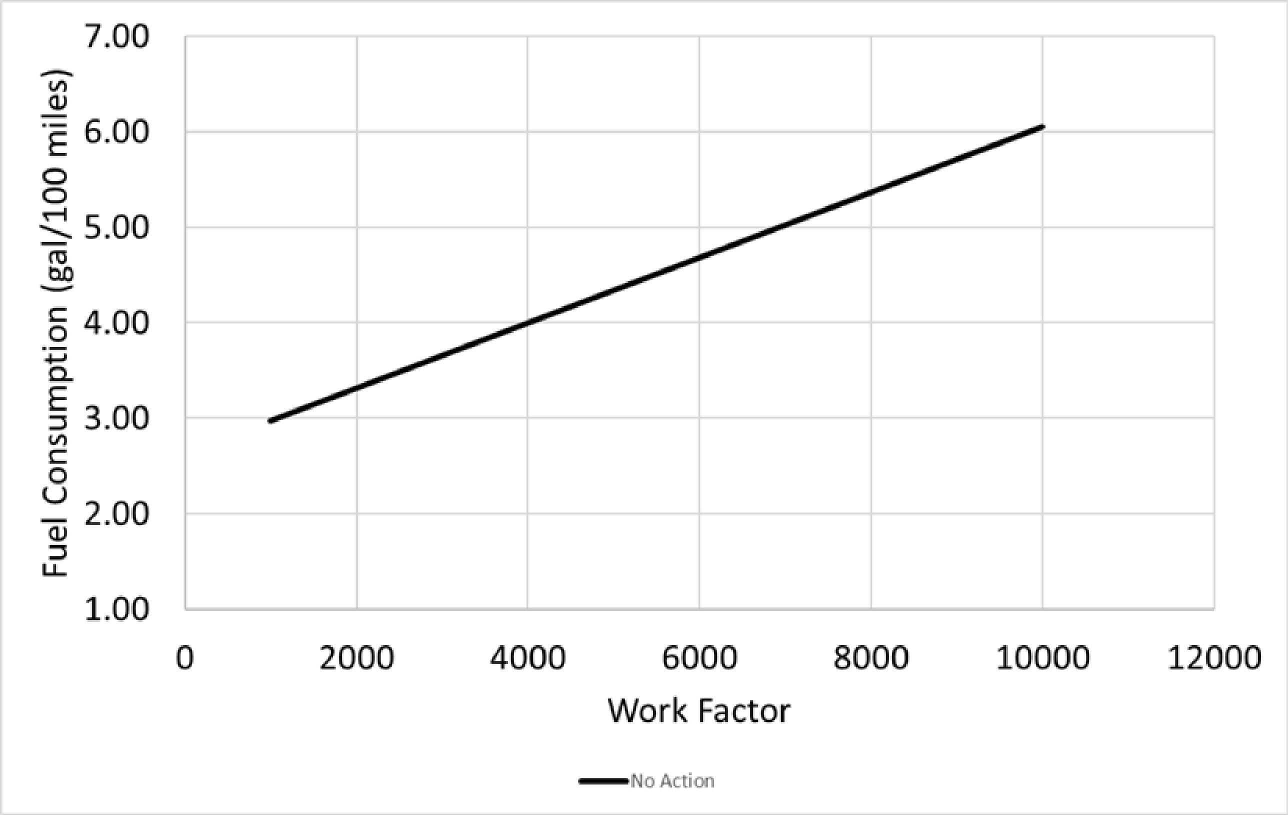
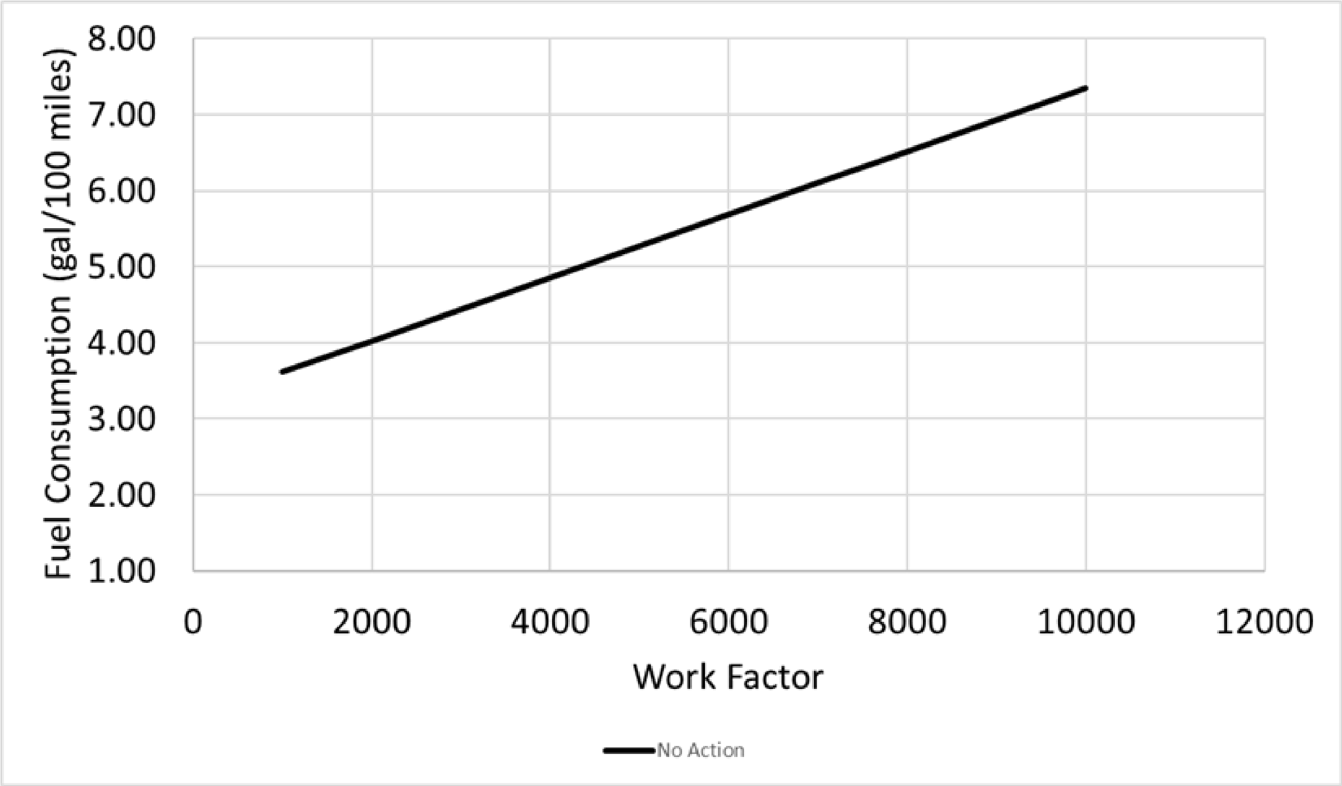


Figure 1-5: No-Action Alternative, HDPUV – SI Vehicles, Target Curves



As the reference baseline scenario, the No-Action Alternative also includes the following other actions that NHTSA believes will occur in the absence of further regulatory action by NHTSA:

To account for the existing national GHG emissions standards, the No-Action Alternative for passenger cars and light trucks includes the following coefficients defining the GHG standards set by EPA in 2022 for model year 2026, which (for purposes of this analysis) are assumed to persist without change in subsequent MYs:

Table 1-10: Passenger Car CO_2 Target Function Coefficients for No-Action Alternative

	2027	2028	2029	2030	2031	2032
a (g/mi)	114.3	114.3	114.3	114.3	114.3	114.3
b (g/mi)	160.9	160.9	160.9	160.9	160.9	160.9
c (g/mi per s.f.)	3.11	3.11	3.11	3.11	3.11	3.11
d (g/mi)	-13.10	-13.10	-13.10	-13.10	-13.10	-13.10
e (s.f.)	41.0	41.0	41.0	41.0	41.0	41.0
f (s.f.)	56.0	56.0	56.0	56.0	56.0	56.0

Table 1-11: Light Truck CO_2 Target Function Coefficients for No-Action Alternative

	2027	2028	2029	2030	2031	2032
a (g/mi)	141.8	141.8	141.8	141.8	141.8	141.8
b (g/mi)	254.4	254.4	254.4	254.4	254.4	254.4
c (g/mi per s.f.)	3.41	3.41	3.41	3.41	3.41	3.41
d (g/mi)	1.90	1.90	1.90	1.90	1.90	1.90
e (s.f.)	41.0	41.0	41.0	41.0	41.0	41.0
f (s.f.)	74.0	74.0	74.0	74.0	74.0	74.0

Coefficients *a*, *b*, *c*, *d*, *e*, and *f* define the existing model year 2026 federal CO_2 standards for passenger cars and light trucks, respectively, in Table 1-10 and Table 1-11 above. Analogous to coefficients defining CAFE standards, coefficients *a* and *b* specify minimum and maximum CO_2 targets in each model year. Coefficients *c* and *d* specify the slope and intercept of the linear portion of the CO_2 target function, and coefficients *e* and *f* bound the region within which CO_2 targets are defined by this linear form.

To account for the 2016 NHTSA/EPA Phase 2 national CO_2 emission standards, the No-Action Alternative for HDPUVs include the following coefficients defining the WF based standards set by EPA for the model year 2027 and beyond. The four-wheel drive coefficient is maintained at 500 (coefficient 'a') and the weighting multiplier coefficient is maintained at 0.75 (coefficient 'b'). The CI and SI coefficients are in the tables below:

Table 1-12: HDPUV CI Vehicle CO_2 Target Function Coefficients for No-Action Alternative

	2027 and Later
e	0.0348
f	268

Table 1-13: HDPUV SI CO_2 Vehicle Target Function Coefficients for No-Action Alternative

	2027 and Later
c	0.0369
d	284

Coefficients c, d, e, and f define the existing model year 2027 and beyond CO_2 standards from the Phase 2 final rule for HDPUVs, in Table 1-12 and Table 1-13 above. The coefficients define a linear work-factor based function with c and d representing gasoline, CNG vehicles, strong hybrid electric vehicles (SHEVs), and PHEVs and e and f representing diesels, BEVS and fuel cell electric vehicles (FCEV)s. For this rule, this is identical to the NHTSA's fuel efficiency standards No-Action Alternative.

The No-Action Alternative also includes NHTSA's estimates of ways that each manufacturer could introduce new PHEVs and BEVs in response to state ZEV programs.[61] Vehicle manufacturers told NHTSA, in CBI conversations regarding planned vehicle product and technology investments, that they are complying with and plan to comply in the future with ZEV programs. These conversations were later confirmed by manufacturers' public announcements, which are discussed in more detail in preamble Section IV. Therefore, NHTSA has included in the main provisions of the ACC and ACT programs in the CAFE Models' analysis of compliance pathways. Incorporating these programs into the model includes converting vehicles that have been identified as potential ZEV candidates into BEVs so that a manufacturer's fleet meets the calculated ZEV credit requirements. The CAFE Model brings manufacturers into compliance with ACC and ACT and their deployment commitments consistent with ACC II's targets first in the reference baseline, then solves for the technology compliance pathway used to meet increasing ZEV standards described by the state programs. The two programs have different requirements per model year, so they are modeled separately in the CAFE analysis. Chapter 2 below discusses, in detail, how NHTSA developed these estimates.

The No-Action Alternative also includes NHTSA's estimates of ways that manufacturers could take advantage of recently-passed tax credits for battery-based vehicle technologies. NHTSA explicitly models portions of three provisions of the IRA when simulating the behavior of manufacturers and consumers. The first is the Advanced Manufacturing Production Tax Credit (AMPC). The AMPC also includes a credit for the production of applicable critical minerals. This provision of the IRA provides a $35 per kWh tax credit for manufacturers of battery cells and an additional $10 per kWh for manufacturers of battery modules (all applicable to manufacture in the United States).[62] These credits, with the exception of the critical minerals credit, phase out from 2030 to 2032. The agency also jointly modeled the Clean Vehicle Credit (CVC),[63] which provides up to $7,500 toward the purchase of clean vehicles.[64] The AMPC and CVC provide tax credits for light-duty and HDPUV PHEVs, BEVS, and FCEVs. Chapter 2.2 below discusses, in detail, how NHTSA has modeled these tax credits.

The No-Action Alternative for the passenger car, light truck and HDPUV fleets also includes NHTSA's assumption, for purposes of compliance simulations, that manufacturers will add fuel economy- or fuel efficiency-improving technology voluntarily, if the value of future undiscounted fuel savings fully offsets the cost of the technology within 30 months. This assumption is often called the "30-month payback" assumption, and NHTSA has used it for many years and in many CAFE rulemakings.[65] It is used to represent consumer demand for fuel economy. It can be a source of apparent "over-compliance" in the No-Action Alternative, especially when technology is estimated to be extremely cost-effective, as occurs later in the analysis time frame when learning has significant effects on some technology costs.

NHTSA has determined that manufacturers do improve fuel economy even in the absence of new standards, for several reasons. First, overcompliance is not uncommon in the historical data, both in the absence of new standards, and with new standards – NHTSA's analysis in the 2022 TSD included CAFE compliance data

[61] NHTSA interprets EPCA/EISA as allowing consideration of BEVs and PHEVs built in response to state ZEV programs as part of the analytical reference baseline because (1) 49 U.S.C. 32902(h) clearly applies to the "maximum feasible" determination, which is a determination *between* regulatory alternatives, and the reference baseline is simply the backdrop against which that determination is made, and (2) NHTSA continues to believe that it is arbitrary to interpret 32902(h) as requiring NHTSA to pretend that BEVs and PHEVs clearly built for non-CAFE-compliance reasons do not exist, because doing so would be unrealistic and would bias NHTSA's analytical results by inaccurately attributing costs and benefits to future potential CAFE standards that will not accrue as a result of those standards in real life.

[62] 26 U.S.C. 45X. If a manufacturer produces a battery module without battery cells, they are eligible to claim up to $45 per kWh for the battery module. The provision includes other provisions related to vehicles such as a credit equal to 10 percent of the manufacturing cost of electrode active materials, and another 10 percent for the manufacturing cost of critical minerals. We are not modeling these credits directly because of how we estimate battery costs and to avoid the potential to double count the tax credits if they are included into other analyses that feed into our inputs.

[63] 26 U.S.C. 30D.

[64] There are vehicle price and consumer income limitations on the CVC as well. Congressional Research Service. 2022. Tax Provisions in the Inflation Reduction Act of 2022 (H.R. 5376). Available at: https://crsreports.congress.gov/product/pdf/R/R47202/6. (Accessed: Feb. 7, 2024).

[65] Even though NHTSA uses the 30-month payback assumption to assess how much technology manufacturers would add voluntarily in the absence of new standards, the benefit-cost analysis accounts for the full lifetime fuel savings that would accrue to vehicles affected by the final standards.

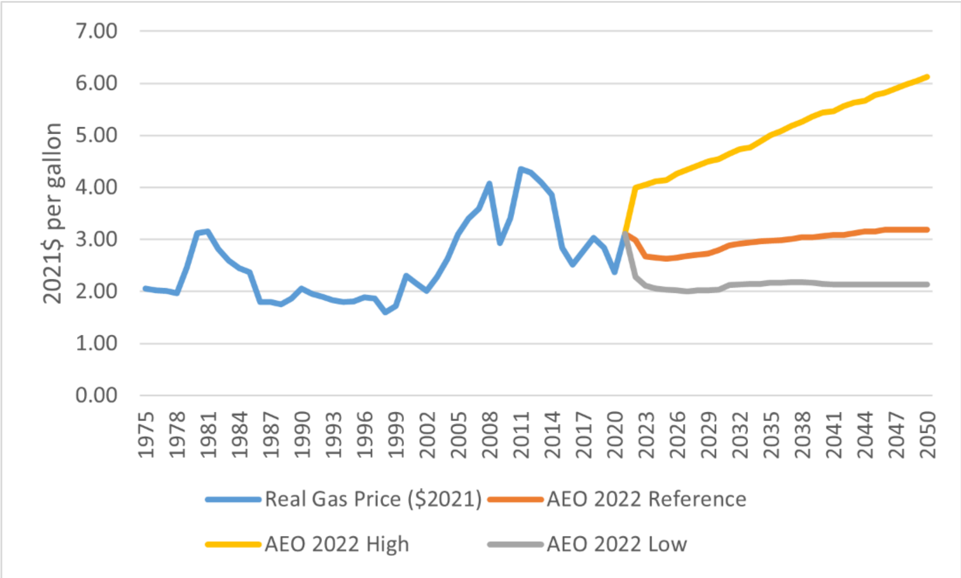
showing that from 2004-2017, while not all manufacturers consistently over-complied, a number did. Of the manufacturers who did over-comply, some did so by 20 percent or more, in some fleets, over multiple model years.[66] Ordinary market forces can produce significant increases in fuel economy, either because of consumer demand or because of technological advances.

Second, manufacturers have consistently told NHTSA that they do make fuel economy improvements where the cost can be fully recovered by consumers in the first 2-3 years of ownership. The 2015 NAS report discussed this assumption explicitly, stating: “There is also empirical evidence supporting loss aversion as a possible cause of the energy paradox. Greene (2011) showed that if consumers accurately perceived the upfront cost of fuel economy improvements and the uncertainty of fuel economy estimates, the future price of fuel, and other factors affecting the present value of fuel savings, the loss-averse consumers among them would appear to act as if they had very high discount rates or required payback periods of about 3 years.”[67] Furthermore, the 2020 NAS heavy-duty report states: ”The committee has heard from manufacturers and purchasers that they look for 1.5- to 2-year paybacks or, in other cases, for a payback period that is half the expected ownership period of the first owner of the vehicle.”[68] Naturally, there are heterogenous preferences for vehicle attributes in the marketplace, – at the same time that we are observing record sales of electrified vehicles, we are also seeing sustained demand for pickup trucks with higher payloads and towing capacity and hence lower fuel economy. This analysis, like all the CAFE analyses preceding it, uses an average value to represent these preferences for the CAFE fleet and the HDPUV fleet. The analysis balances the risks of estimating too low of a payback period, which would preclude most technologies from consideration regardless of potential cost reductions due to learning, against the risk of allowing too high of a payback period, which would allow an unrealistic cost increase from technology addition in the reference baseline fleet.

Third, as in previous CAFE analyses, our fuel price projections assume sustained increases in real fuel prices over the course of the rule (and beyond). As readers are certainly aware, fuel prices have changed over time – sometimes quickly, sometimes slowly, but generally over time upward:

[66] See 2022 TSD, at 68.
[67] National Research Council. 2015. Cost, Effectiveness, and Deployment of Fuel Economy Technologies for Light-Duty Vehicles. Washington, D.C: *The National Academies Press.* p. 31. Available at: https://nap.nationalacademies.org/catalog/21744/cost-effectiveness-and-deployment-of-fuel-economy-technologies-for-light-duty-vehicles. (Accessed: Feb. 7, 2024). (hereinafter, "2015 NAS report").
[68] National Academies of Sciences, Engineering, and Medicine. 2020. Reducing Fuel Consumption and Greenhouse Gas Emissions of Medium- and Heavy-Duty Vehicles, Phase Two: Final Report. Washington, D.C: *The National Academies Press*. p. 296. Available at: https://nap.nationalacademies.org/catalog/25542/reducing-fuel-consumption-and-greenhouse-gas-emissions-of-medium-and-heavy-duty-vehicles-phase-two. (Accessed: Feb 7, 2024).

Figure 1-6: Real Fuel Prices Over Time



In the 1990s, when fuel prices were historically low (as shown above), manufacturers did not tend to improve their fuel economy, likely because there simply was very little consumer demand for improved fuel economy and CAFE standards remained flat. In subsequent decades, when fuel prices were higher, many of them have exceeded their standards in multiple fleets, and for multiple years. Our current fuel price projections look more like the last two decades, where prices have been more volatile, but also closer to $3/gallon on average. In recent years, when fuel prices have generally declined on average and CAFE standards have continued to increase, fewer manufacturers have exceeded their standards. However, our compliance data show that at least some manufacturers do improve their fuel economy if fuel prices are high enough, even if they are not able to respond perfectly to fluctuations precisely when they happen. This highlights the importance of fuel price assumptions both in the analysis and in the real world on the future of fuel economy improvements.

1.4.2. Alternative Baseline/No-Action Alternative

In addition to the reference baseline for the passenger car and light truck fleet analysis, NHTSA considered an alternative baseline analysis. This alternative baseline analysis for the passenger car and light truck fleets was performed to provide a greater level of insight into the possibilities of a changing baseline landscape. The Alternative Baseline analysis is not meant to be a replacement for the reference analysis, but a secondary review of the NHTSA analysis with all of the assumptions from the reference baseline held (see Paragraph 1.4.1 above), except for the assumption of compliance with CARB ZEV policies. The alternative baseline does not assume manufacturers will consider or preemptively react to any of the California light duty ZEV policies either during any of the model years simulated in the analysis, regardless of whether it becomes a legally binding program.

1.4.3. Action Alternatives for Passenger Cars, Light Trucks, and HDPUVs

In addition to the No-Action Alternatives, NHTSA has considered five “action” alternatives for passenger cars and light trucks and four action alternatives for HDPUVs, each of which is more stringent than the No-Action Alternative during the rulemaking time frame. These action alternatives are specified below and demonstrate different possible approaches to balancing the statutory factors applicable for passenger cars, light trucks, and HDPUVs. Section VI of the final rule preamble discusses in more detail how the different alternatives reflect different possible balancing approaches.

1.4.3.1. Alternative PC1LT3

Alternative PC1LT3 would increase CAFE stringency by 1 percent per year, year over year for model years 2027-2032 passenger cars, and by 3 percent per year, year over year for model years 2027-2032 light trucks.

Table 1-14: Passenger Car CAFE Target Function Coefficients for Alternative PC1LT3[69]

	2027	2028	2029	2030	2031	2032 (augural)
a (mpg)	67.63	68.31	69.00	69.70	70.40	71.11
b (mpg)	50.60	51.11	51.63	52.15	52.68	53.21
c (gpm per s.f.)	0.00033176	0.00032845	0.00032516	0.00032191	0.00031869	0.00031550
d (gpm)	0.00118417	0.00117232	0.00116060	0.00114900	0.00113751	0.00112613

Table 1-15: Light Truck CAFE Target Function Coefficients for Alternative PC1LT3[70]

	2027	2028	2029	2030	2031	2032 (augural)
a (mpg)	55.39	57.10	58.87	60.69	62.56	64.50
b (mpg)	33.30	34.33	35.39	36.48	37.61	38.78
c (gpm per s.f.)	0.00036296	0.00035207	0.00034151	0.00033126	0.00032132	0.00031168
d (gpm)	0.00317343	0.00307823	0.00298588	0.00289630	0.00280941	0.00272513

These equations are represented graphically below:

[69] The Function Coefficients ‘a’,’b’,’c’, and ‘d’ are defined in Equation 1-1 of Chapter 1.2.1.
[70] The Function Coefficients ‘a’,’b’,’c’, and ‘d’ are defined in Equation 1-1 of Chapter 1.2.1.

Figure 1-7: Alternative PC1LT3, Passenger Car Fuel Economy, Target Curves

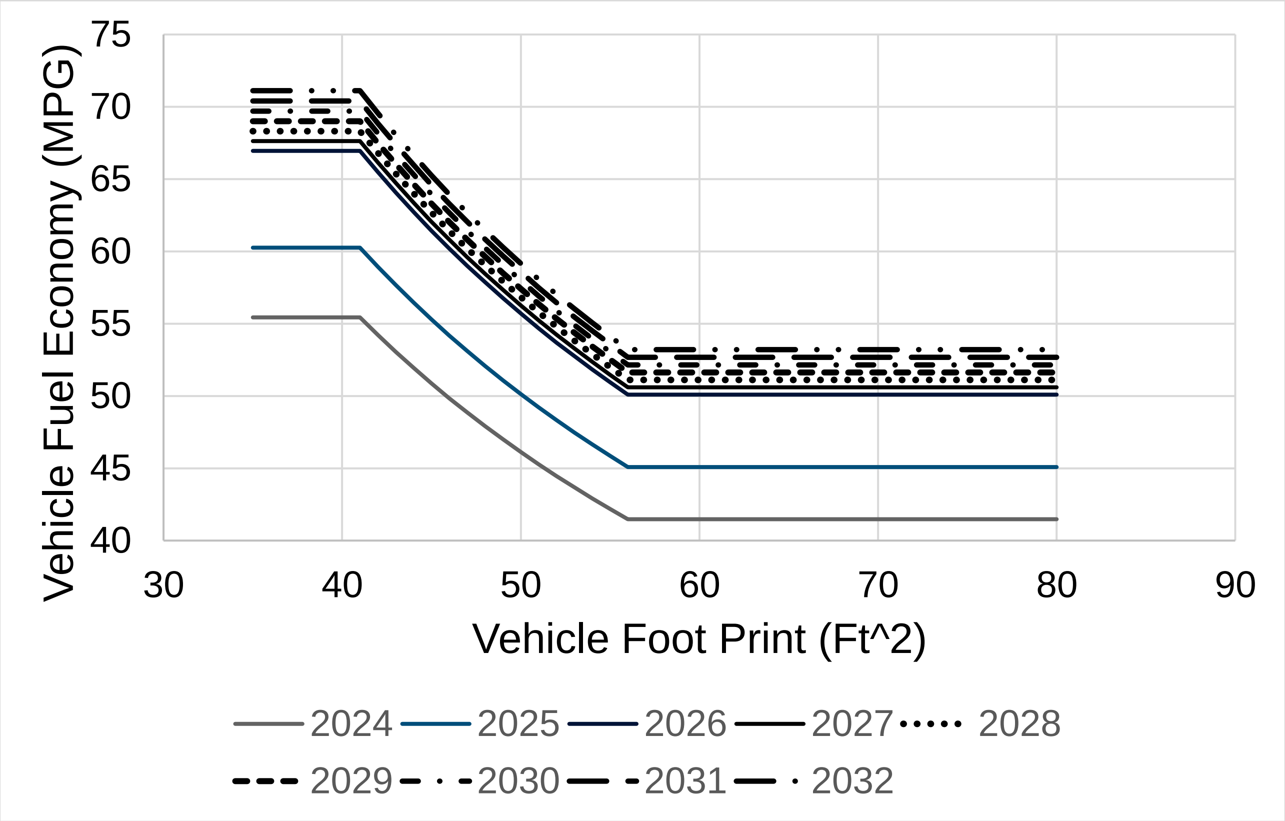
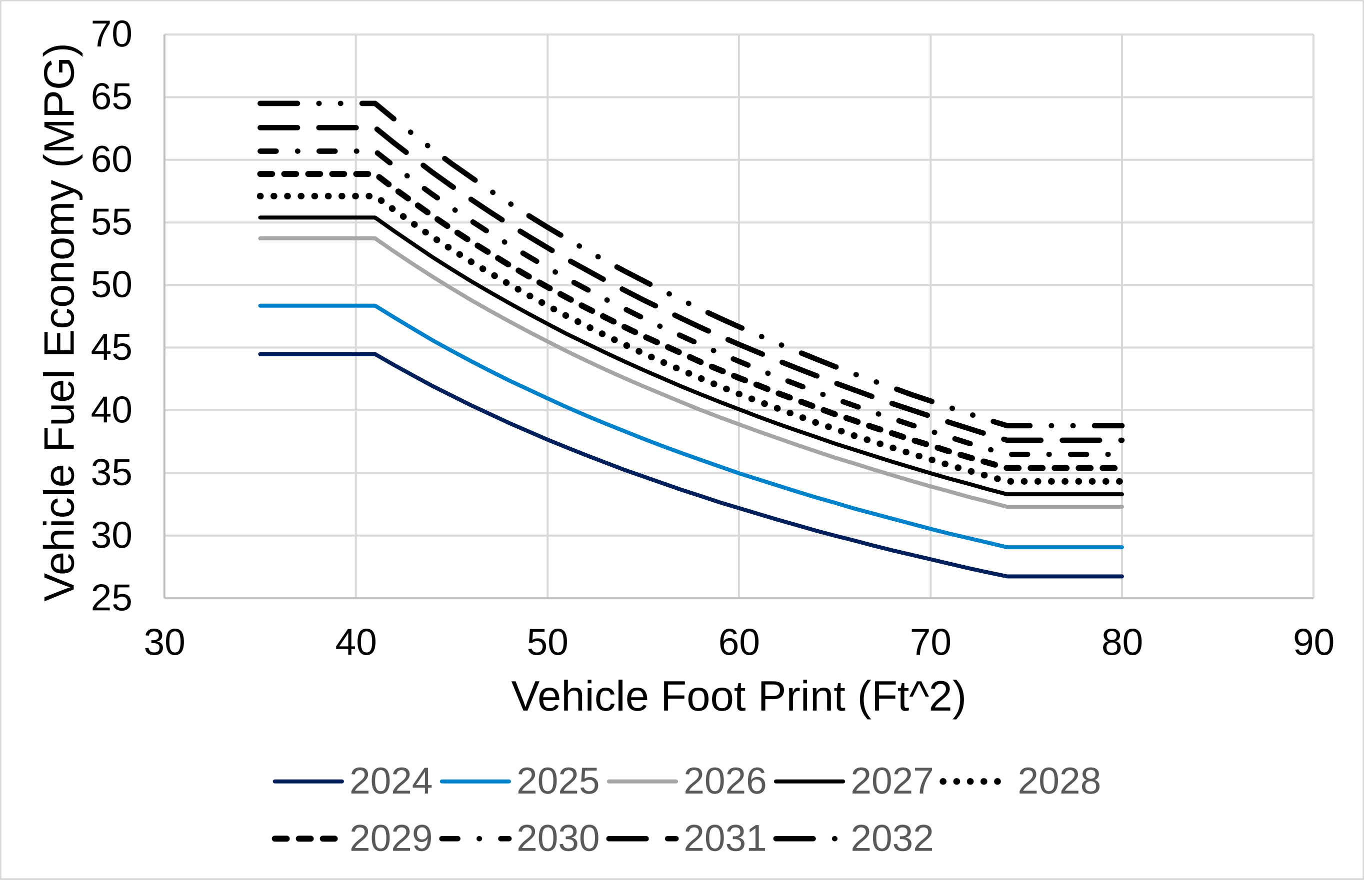


Figure 1-8: Alternative PC1LT3, Light Truck Fuel Economy, Target Curves



Under this alternative, the MDPCS is as follows:

Table 1-16: Alternative PC1LT3 – Minimum Domestic Passenger Car Standard (MPG)

2027	2028	2029	2030	2031	2032 (augural)
54.6	55.2	55.7	56.3	56.9	57.4

1.4.3.2. Alternative PC2LT002 – Preferred Alternative

Alternative PC2LT002 would increase CAFE stringency by 2 percent per year, year over year for model years 2027-2032 passenger cars, and by 0 percent per year, year over year for model years 2027-2028 light trucks and then 2 percent per year, year over year for model years 2029-2032 light trucks.

Table 1-17: Passenger Car CAFE Target Function Coefficients for Alternative PC2LT002

	2027	2028	2029	2030	2031	2032 (augural)
a (mpg)	68.32	69.71	71.14	72.59	74.07	75.58
b (mpg)	51.12	52.16	53.22	54.31	55.42	56.55
c (gpm per s.f.)	0.00032841	0.00032184	0.00031541	0.00030910	0.00030292	0.00029686
d (gpm)	0.00117220	0.00114876	0.00112579	0.00110327	0.00108120	0.00105958

Table 1-18: Light Truck CAFE Target Function Coefficients for Alternative PC2LT002

	2027	2028	2029	2030	2031	2032 (augural)
a (mpg)	53.73	53.73	54.82	55.94	57.08	58.25
b (mpg)	32.30	32.30	32.96	33.63	34.32	35.02
c (gpm per s.f.)	0.00037418	0.00037418	0.00036670	0.00035936	0.00035218	0.00034513
d (gpm)	0.00327158	0.00327158	0.00320615	0.00314202	0.00307918	0.00301760

Table 1-19: Alternative PC2LT002 – Minimum Domestic Passenger Car Standard (MPG)

2027	2028	2029	2030	2031	2032 (augural)
55.2	56.3	57.5	58.6	59.8	61.1

Figure 1-9: Alternative PC2LT002, Passenger Car Fuel Economy, Target Curves

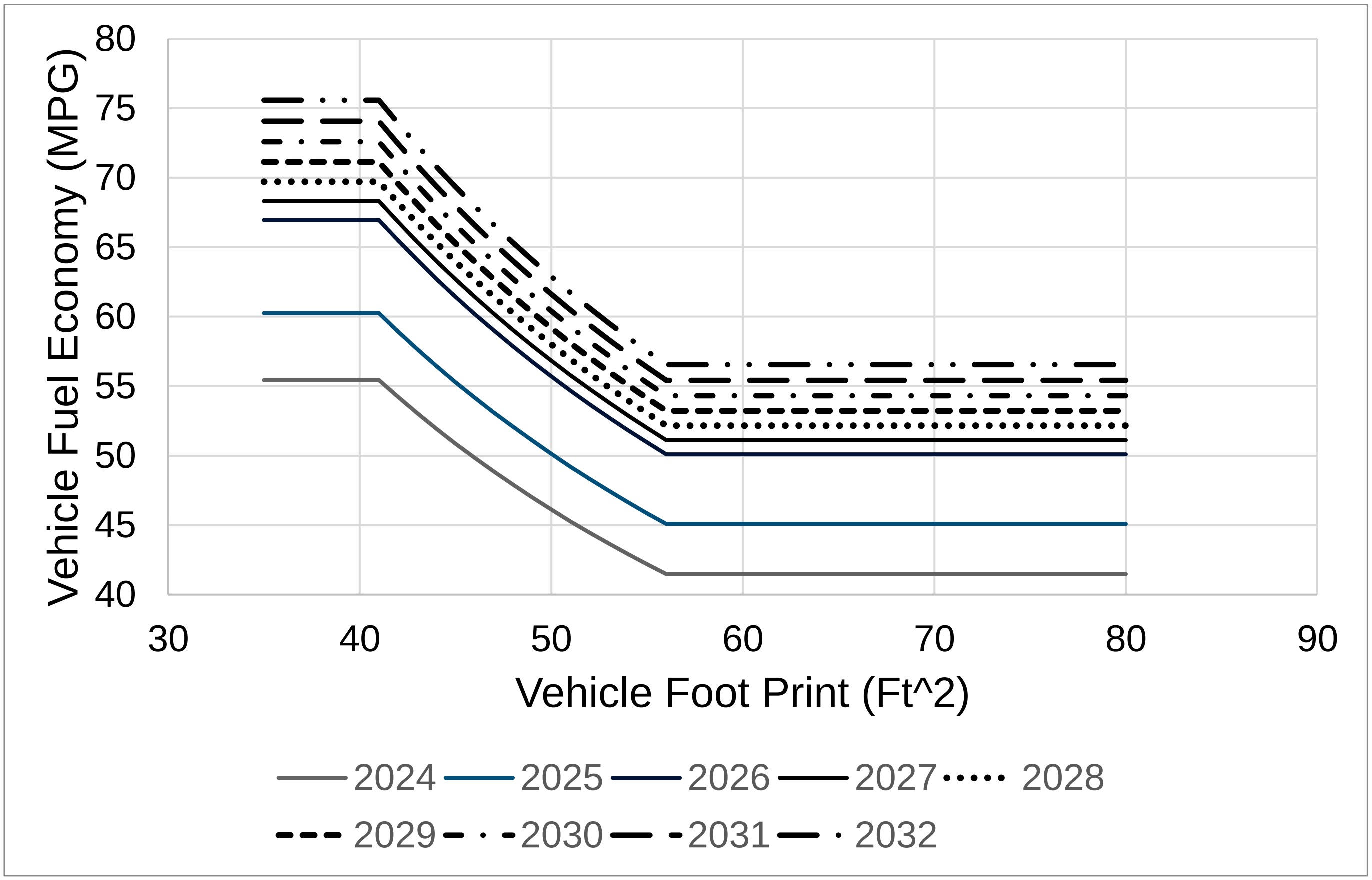
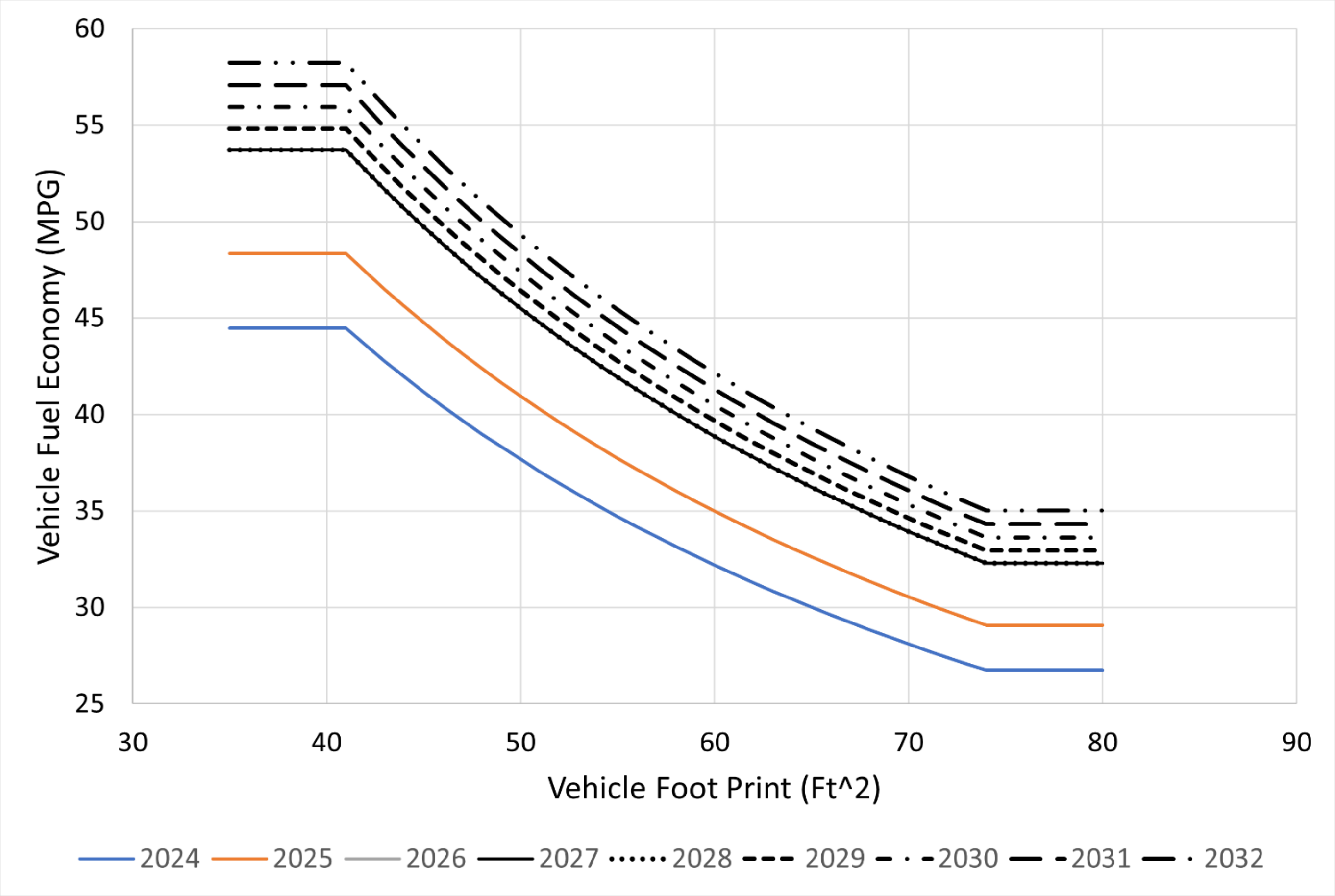


Figure 1-10: Alternative PC2LT002, Light Truck Fuel Economy, Target Curves[71]



1.4.3.3. Alternative PC2LT4

Alternative PC2LT4 would increase CAFE stringency by 2 percent per year, year over year for model years 2027-2032 passenger cars, and by 4 percent per year, year over year for model years 2027-2032 light trucks.

Table 1-20: Passenger Car CAFE Target Function Coefficients for Alternative PC2LT4[72]

	2027	2028	2029	2030	2031	2032 (augural)
a (mpg)	68.32	69.71	71.14	72.59	74.07	75.58
b (mpg)	51.12	52.16	53.22	54.31	55.42	56.55
c (gpm per s.f.)	0.00032841	0.00032184	0.00031541	0.00030910	0.00030292	0.00029686
d (gpm)	0.00117220	0.00114876	0.00112579	0.00110327	0.00108120	0.00105958

Table 1-21: Light Truck CAFE Target Function Coefficients for Alternative PC2LT4[73]

	2027	2028	2029	2030	2031	2032 (augural)
a (mpg)	55.96	58.30	60.73	63.26	65.89	68.64

[71] This figure has MYs 2026,2027, and 2028 standards overlaid
[72] The Function Coefficients 'a','b','c', and 'd' are defined in Equation 1-1 of Chapter 1.2.1.
[73] The Function Coefficients 'a','b','c', and 'd' are defined in Equation 1-1 of Chapter 1.2.1.

b (mpg)	33.64	35.05	36.51	38.03	39.61	41.26
c (gpm per s.f.)	0.00035921	0.00034485	0.00033105	0.00031781	0.00030510	0.00029289
d (gpm)	0.00314071	0.00301509	0.00289448	0.00277870	0.00266755	0.00256085

These equations are represented graphically below:

Figure 1-11: Alternative PC2LT4, Passenger Car Fuel Economy, Target Curves

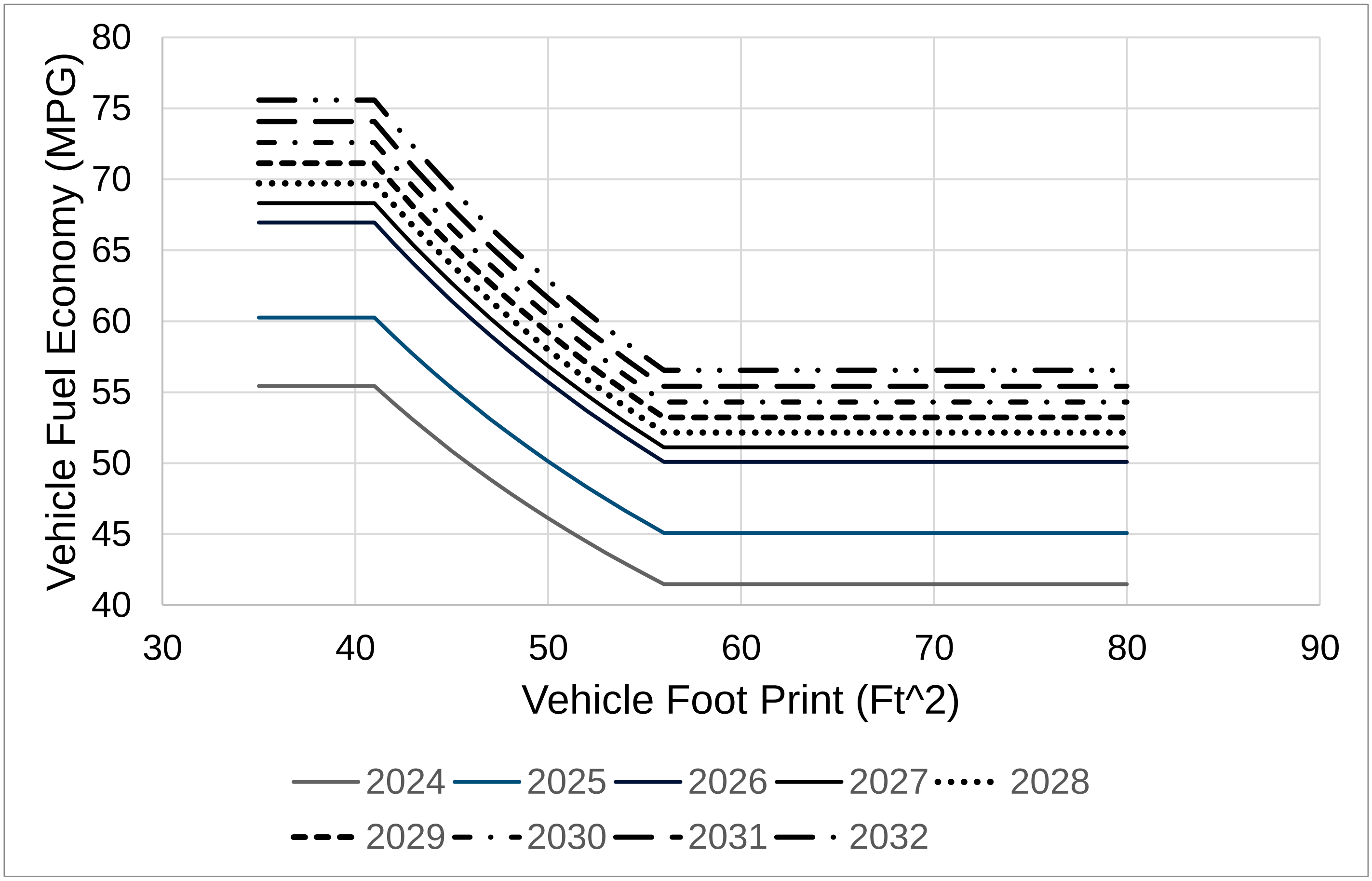
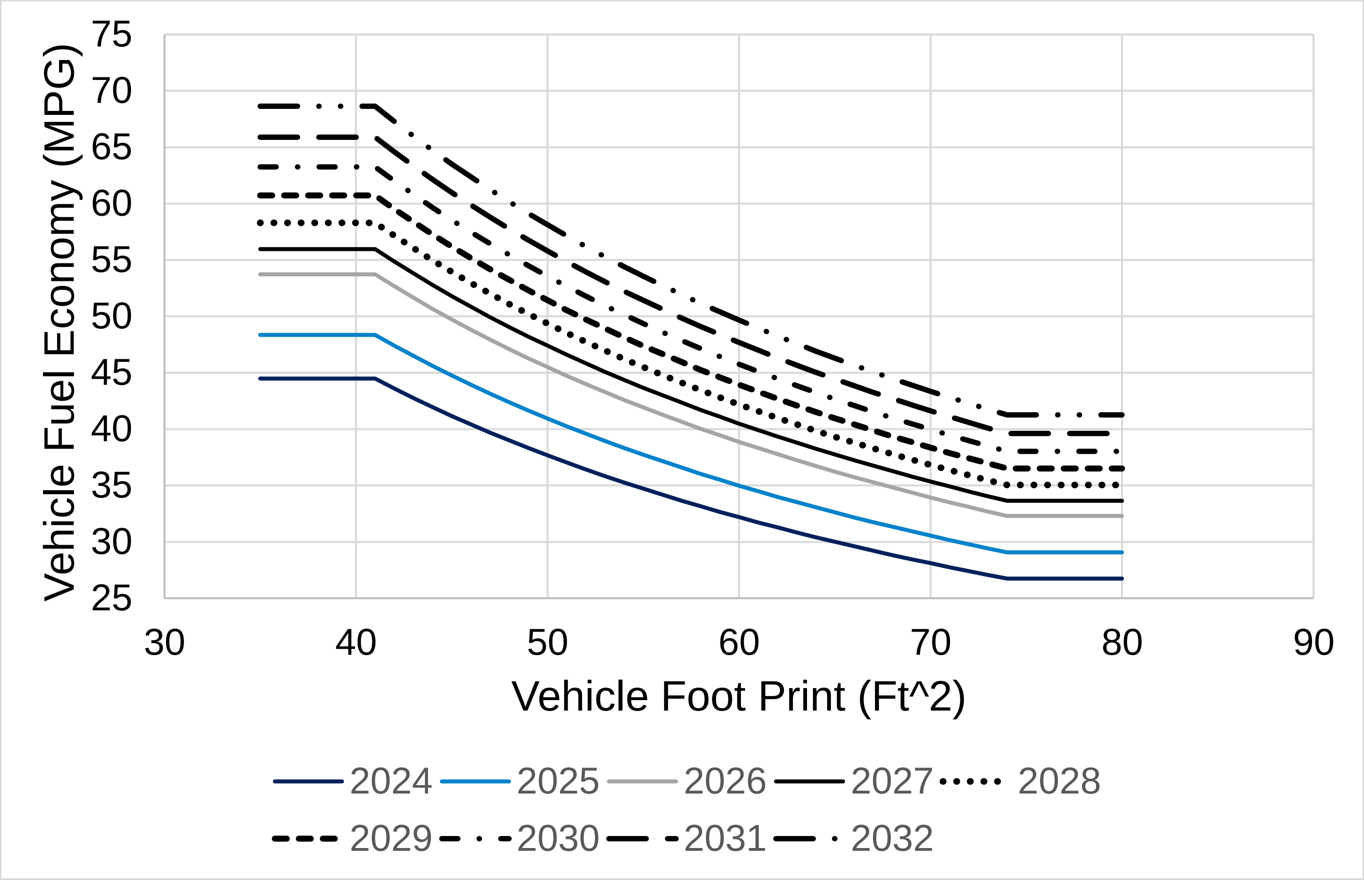


Figure 1-12: Alternative PC2LT4, Light Truck Fuel Economy, Target Curves



Under this alternative, the MDPCS is as follows:

Table 1-22: Alternative PC2LT4 – Minimum Domestic Passenger Car Standard (MPG)

2027	2028	2029	2030	2031	2032 (augural)
55.2	56.3	57.5	58.6	59.8	61.1

1.4.3.4. Alternative PC3LT5

Alternative PC3LT5 would increase CAFE stringency by 3 percent per year, year over year for model years 2027-2032 passenger cars, and by 5 percent per year, year over year for model years 2027-2032 light trucks.

Table 1-23: Passenger Car CAFE Target Function Coefficients for Alternative PC3LT5[74]

	2027	2028	2029	2030	2031	2032 (augural)
a (mpg)	69.02	71.16	73.36	75.63	77.97	80.38
b (mpg)	51.64	53.24	54.89	56.58	58.33	60.14
c (gpm per s.f.)	0.00032506	0.00031531	0.00030585	0.00029668	0.00028777	0.00027914
d (gpm)	0.00116024	0.00112544	0.00109167	0.00105892	0.00102716	0.00099634

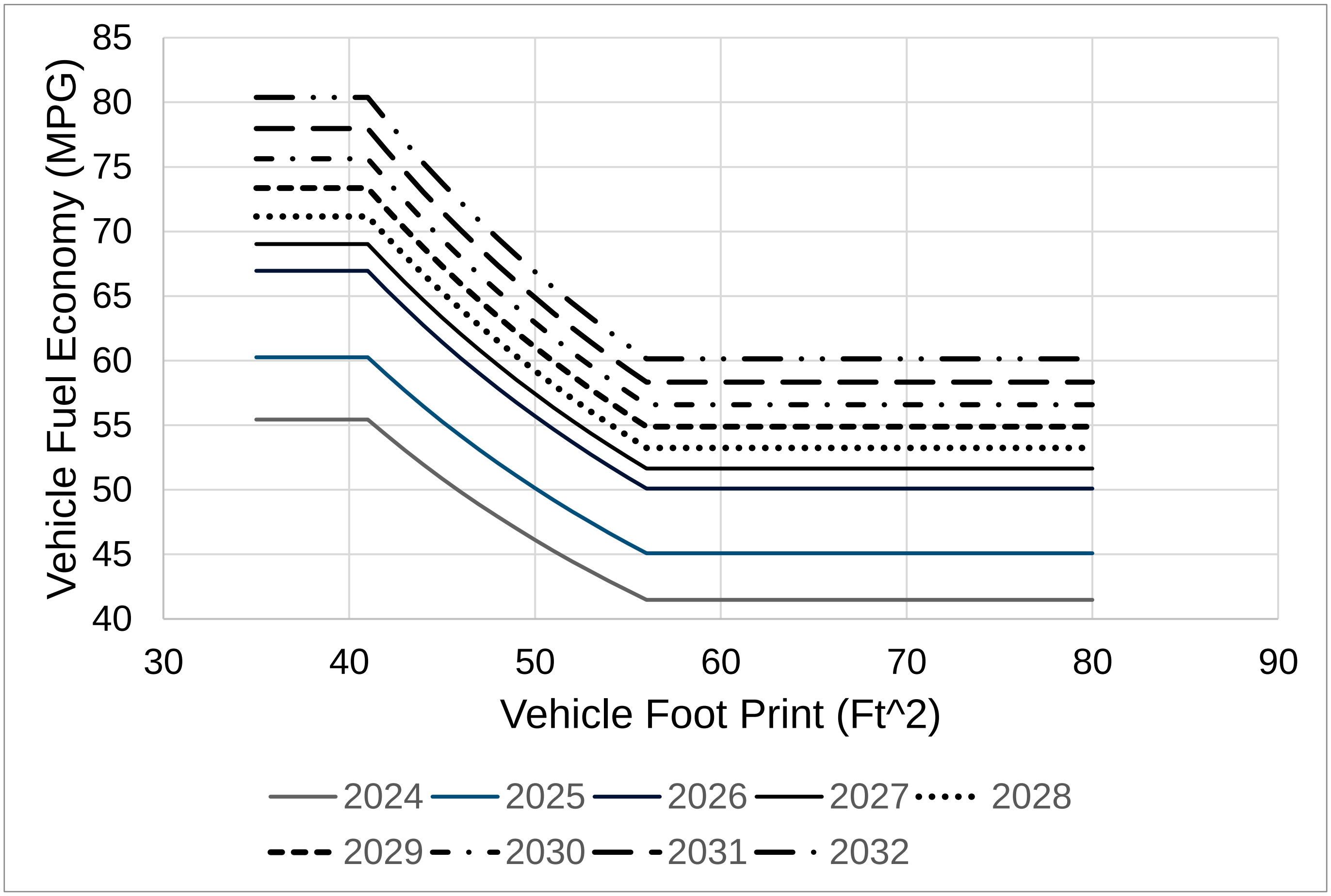
[74] The Function Coefficients 'a','b','c', and 'd' are defined in Equation 1-1 of Chapter 1.2.1.

Table 1-24: Light Truck CAFE Target Function Coefficients for Alternative PC3LT5[75]

	2027	2028	2029	2030	2031	2032 (augural)
a (mpg)	56.55	59.53	62.66	65.96	69.43	73.09
b (mpg)	34.00	35.79	37.67	39.65	41.74	43.94
c (gpm per s.f.)	0.00035547	0.00033770	0.00032081	0.00030477	0.00028954	0.00027506
d (gpm)	0.00310800	0.00295260	0.00280497	0.00266472	0.00253148	0.00240491

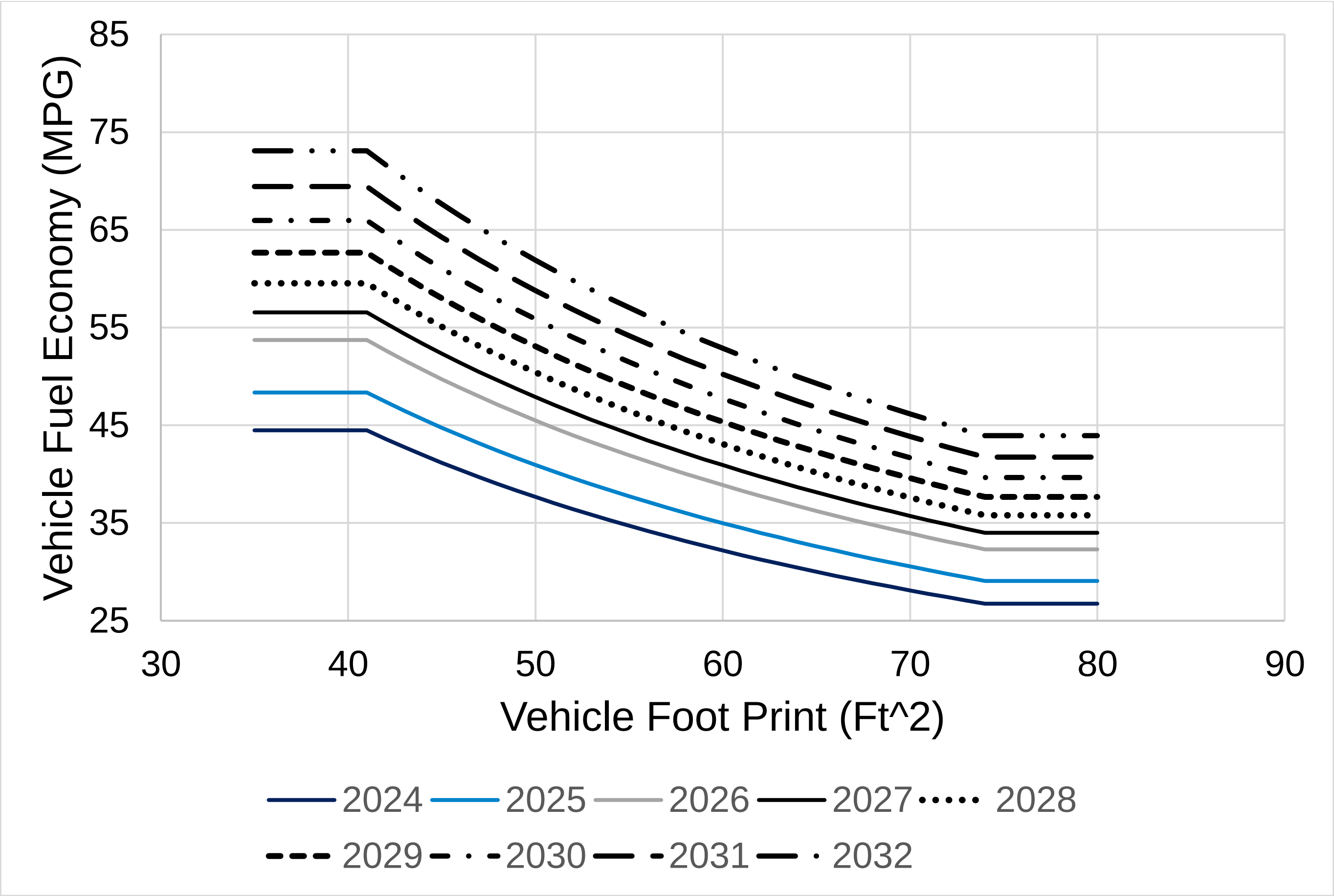
These equations are represented graphically below:

Figure 1-13: Alternative PC3LT5, Passenger Car Fuel Economy, Target Curves



[75] The Function Coefficients 'a','b','c', and 'd' are defined in Equation 1-1 of Chapter 1.2.1.

Figure 1-14: Alternative PC3LT5, Light Truck Fuel Economy, Target Curves



Under this alternative, the MDPCS is as follows:

Table 1-25: Alternative PC3LT5 – Minimum Domestic Passenger Car Standard (MPG)

2027	2028	2029	2030	2031	2032 (augural)
55.8	57.5	59.3	61.1	63.0	64.9

1.4.3.5. Alternative PC6LT8

Alternative PC6LT8 would increase CAFE stringency by 6 percent per year, year over year for model years 2027-2032 passenger cars, and by 8 percent per year, year over year for model years 2027-2032 light trucks.

Table 1-26: Passenger Car CAFE Target Function Coefficients for Alternative PC6LT8[76]

	2027	2028	2029	2030	2031	2032 (augural)
a (mpg)	71.23	75.77	80.61	85.75	91.23	97.05
b (mpg)	53.29	56.69	60.31	64.16	68.26	72.61
c (gpm per s.f.)	0.00031501	0.00029611	0.00027834	0.00026164	0.00024594	0.00023119

[76] The Function Coefficients 'a','b','c', and 'd' are defined in Equation 1-1 of Chapter 1.2.1.

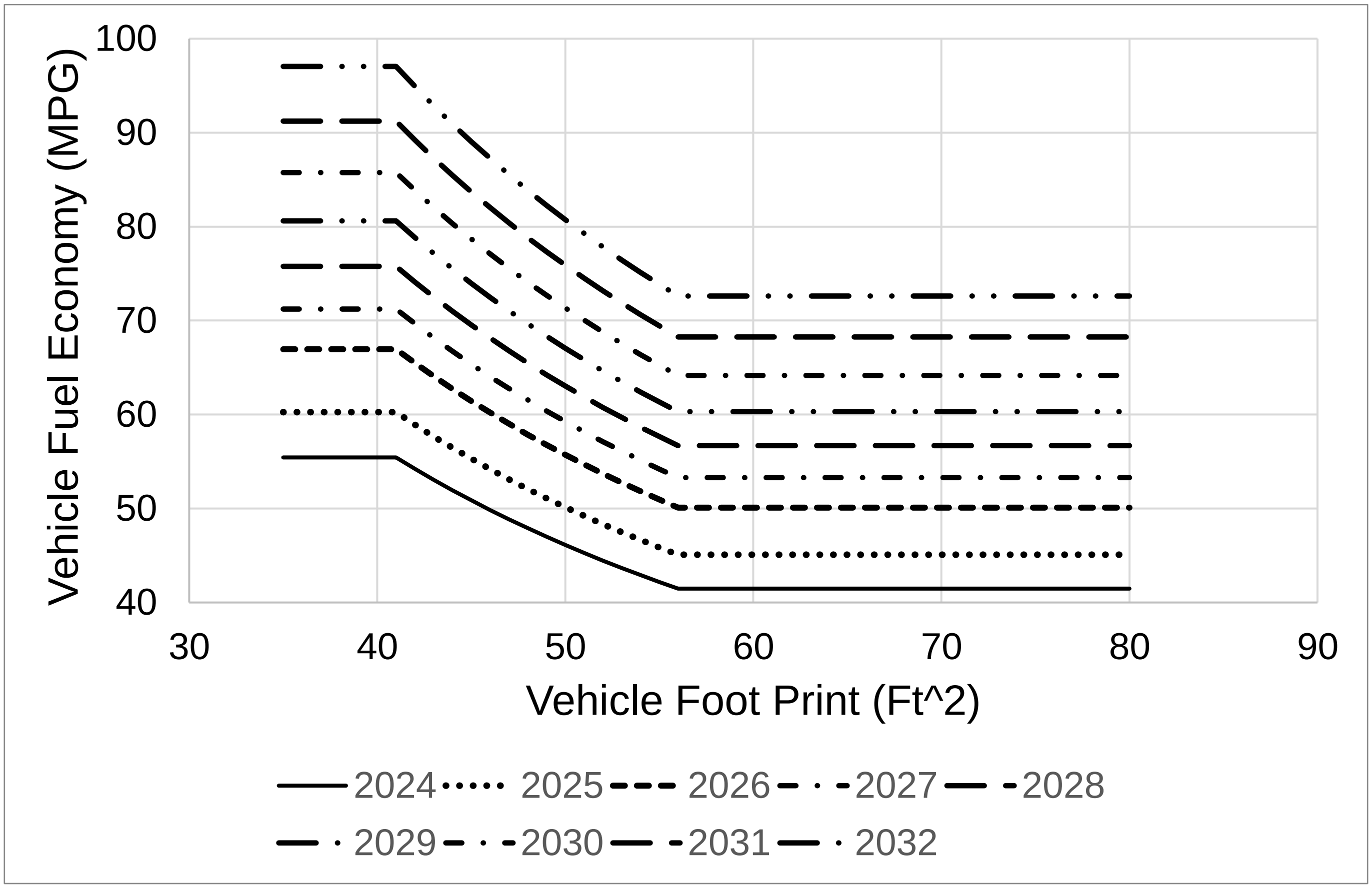
d (gpm)	0.00112436	0.00105690	0.00099348	0.00093388	0.00087784	0.00082517

Table 1-27: Light Truck CAFE Target Function Coefficients for Alternative PC6LT8[77]

	2027	2028	2029	2030	2031	2032 (augural)
a (mpg)	58.40	63.48	69.00	74.99	81.52	88.60
b (mpg)	35.11	38.16	41.48	45.09	49.01	53.27
c (gpm per s.f.)	0.00034425	0.00031671	0.00029137	0.00026806	0.00024662	0.00022689
d (gpm)	0.00300985	0.00276906	0.00254754	0.00234373	0.00215624	0.00198374

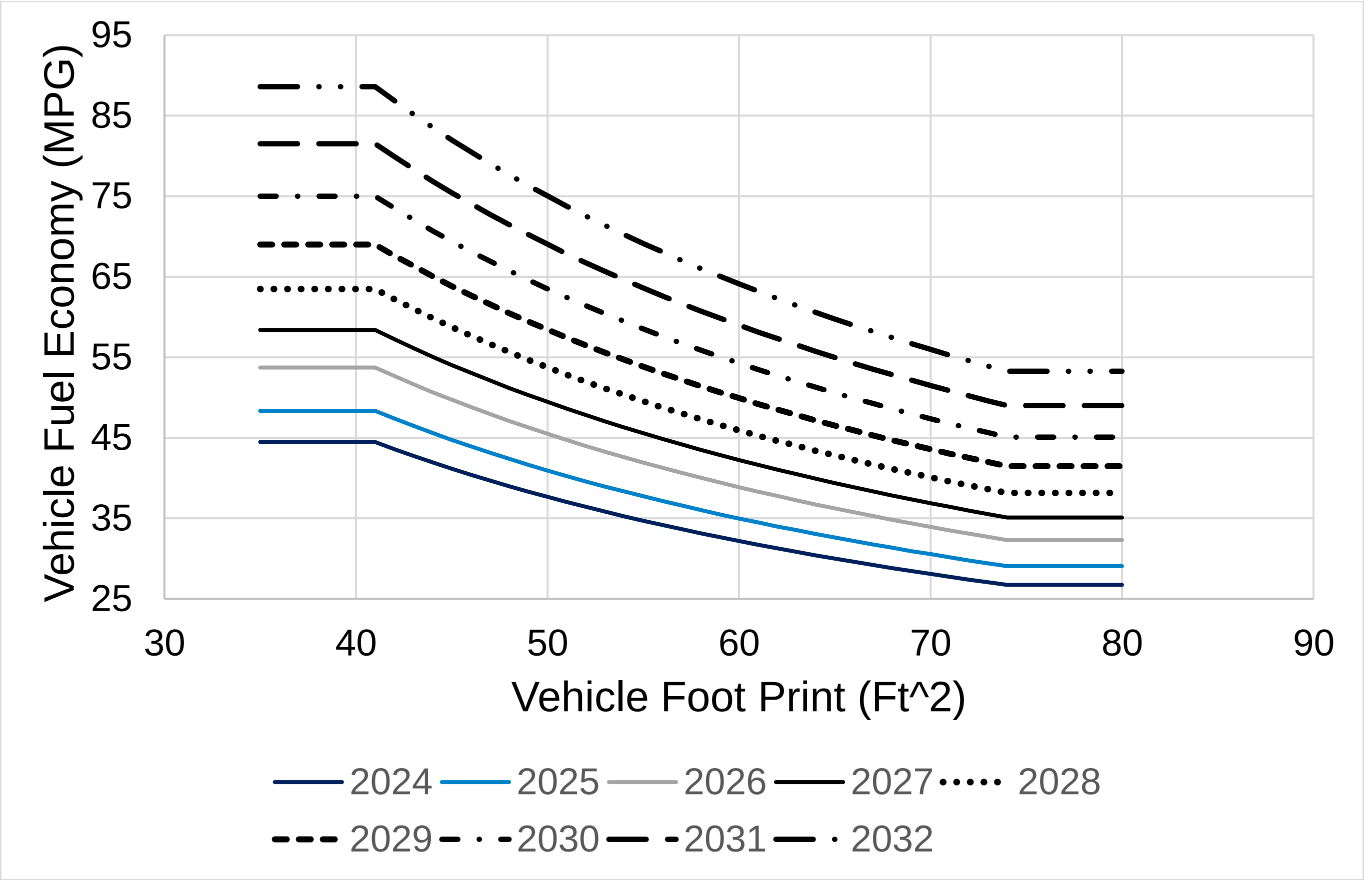
These equations are represented graphically below:

Figure 1-15: Alternative PC6LT8, Passenger Car Fuel Economy, Target Curves



[77] The Function Coefficients 'a','b','c', and 'd' are defined in Equation 1-1 of Chapter 1.2.1.

Figure 1-16: Alternative PC6LT8, Light Truck Fuel Economy, Target Curves



Under this alternative, the MDPCS is as follows:

Table 1-28: Alternative PC6LT8 – Minimum Domestic Passenger Car Standard (MPG)

2027	2028	2029	2030	2031	2032 (augural)
57.5	61.2	65.1	69.3	73.7	78.4

1.4.3.6. Alternative HDPUV4

Alternative HDPUV4 would increase HDPUV standard stringency by 4 percent per year for model years 2030-2035 HDPUVs. The four-wheel drive coefficient is maintained at 500 (coefficient 'a') and the weighting multiplier coefficient is maintained at 0.75 (coefficient 'b').

Table 1-29: Characteristics of Alternative HDPUV4 – CI Vehicle Coefficients[78]

	2030	2031	2032	2033	2034	2035
e	0.00032813	0.00031500	0.00030240	0.00029031	0.00027869	0.00026755
f	2.528	2.427	2.330	2.236	2.147	2.061

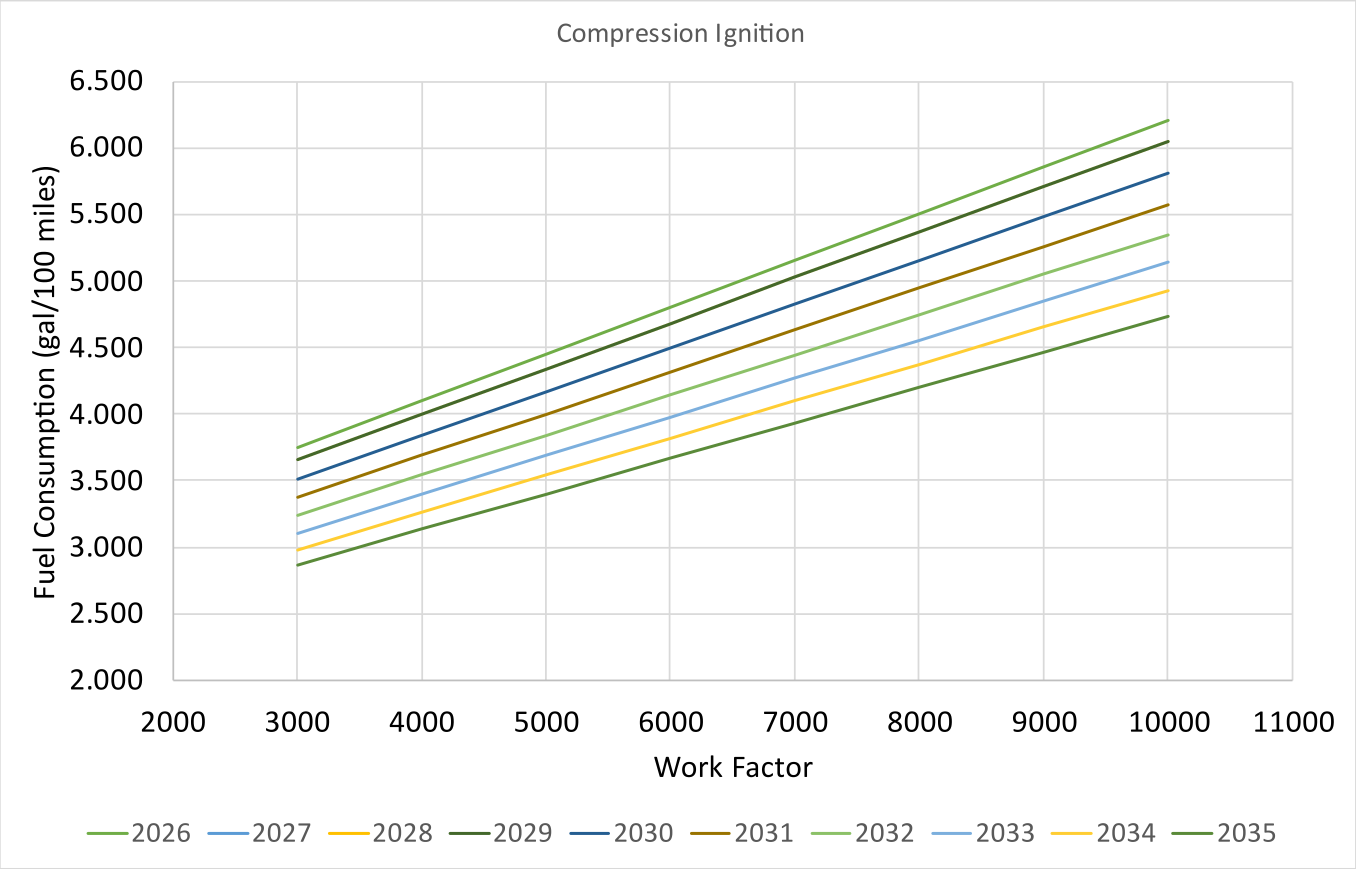
[78] In the CAFE Model, these are Linear work-factor-based function where coefficients e and f are for diesels, BEVs and FCEVs. See Equation 1-3 in Chapter 1.2.1.

Table 1-30: Characteristics of Alternative HDPUV4 – SI Vehicle Coefficients[79]

	2030	2031	2032	2033	2034	2035
c	0.00039859	0.00038265	0.00036734	0.00035265	0.00033854	0.00032500
d	3.068	2.945	2.828	2.715	2.606	2.502

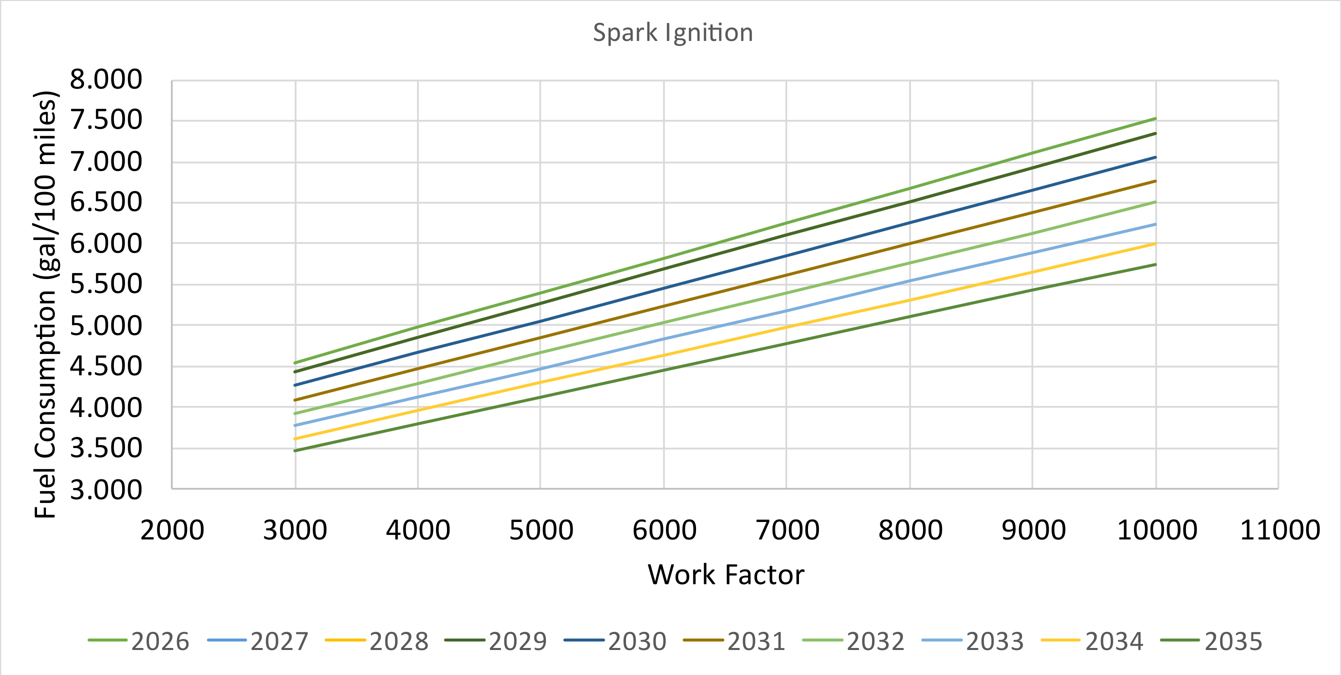
These equations are represented graphically below:

Figure 1-17: Alternative HDPUV4, HDPUV Fuel Efficiency – CI Vehicles, Target Curves



[79] In the CAFE Model, these are Linear work-factor-based function where coefficients c and d are for gasoline, CNG, strong hybrid vehicles and PHEVs. See Equation 1-3 in Chapter 1.2.1.

Figure 1-18: Alternative HDPUV4, HDPUV Fuel Efficiency – SI Vehicles, Target Curves



1.4.3.7. Alternative HDPUV108 – Preferred Alternative

Alternative HDPUV108 would increase HDPUV standard stringency by 10 percent per year, year over year for model years 2030-2032, and by 8 percent per year, year over year for model years 2033-2035 HDPUVs. The four-wheel drive coefficient is maintained at 500 (coefficient ‘a’) and the weighting multiplier coefficient is maintained at 0.75 (coefficient ‘b’).

Table 1-31: Characteristics of Alternative HDPUV108 – CI Vehicle Coefficients[80]

	2030	2031	2032	2033	2034	2035
e	0.00030762	0.00027686	0.00024917	0.00022924	0.00021090	0.00019403
f	2.370	2.133	1.919	1.766	1.625	1.495

Table 1-32: Characteristics of Alternative HDPUV108 – SI Vehicle Coefficients[81]

	2030	2031	2032	2033	2034	2035
c	0.00037368	0.00033631	0.00030268	0.00027847	0.00025619	0.00023569
d	2.876	2.589	2.330	2.143	1.972	1.814

[80] In the CAFE Model, these are linear work-factor-based functions where coefficients e and f are for diesels, BEVs and FCEVs. See Equation 1-3 in Chapter 1.2.1.

[81] In the CAFE Model, these are linear work-factor-based functions where coefficients c and d are for gasoline, CNG, strong hybrid vehicles and PHEVs. See Equation 1-3 in Chapter 1.2.1.

Figure 1-19: Alternative HDPUV108, HDPUV Fuel Efficiency – CI Vehicles, Target Curves

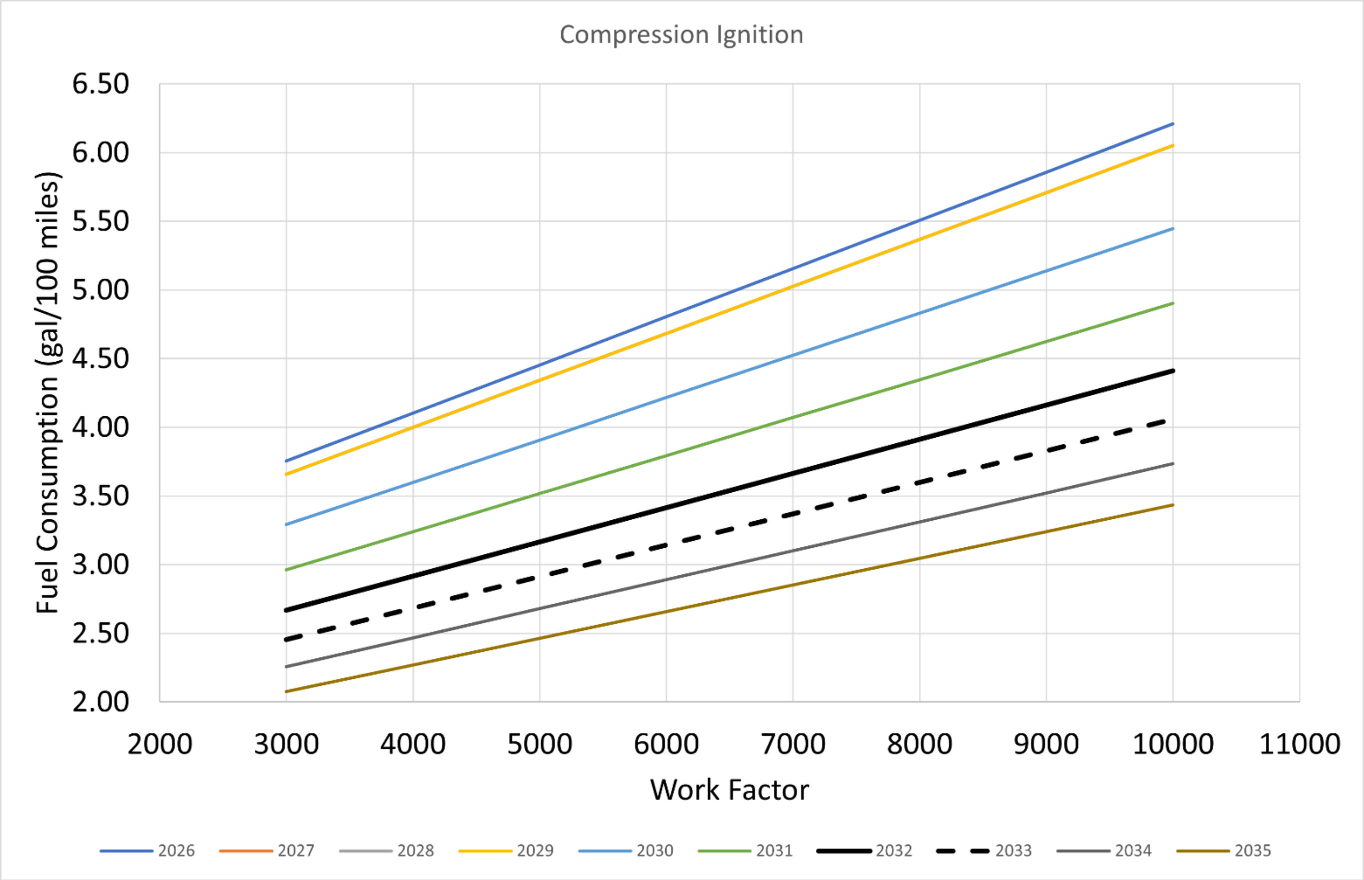
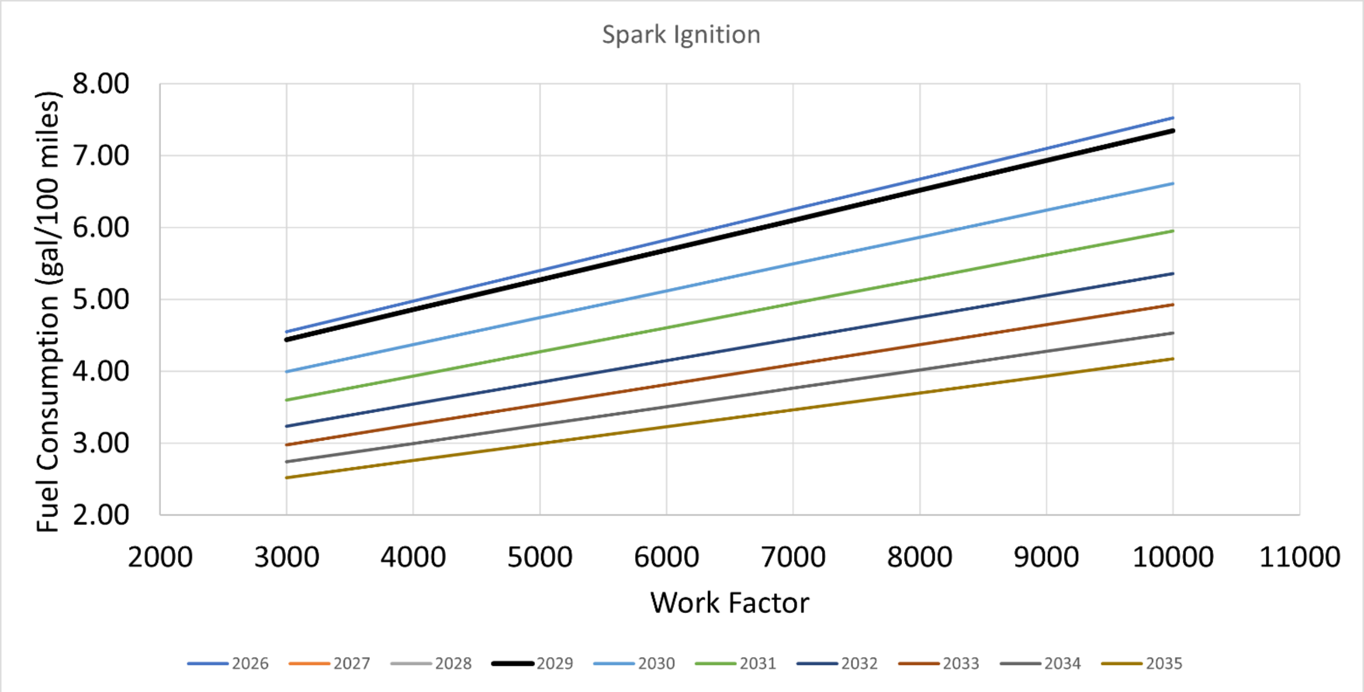


Figure 1-20: Alternative HDPUV108, HDPUV Fuel Efficiency – SI Vehicles, Target Curves



1.4.3.8. Alternative HDPUV10

Alternative HDPUV10 would increase HDPUV standard stringency by 10 percent per year for model years 2030-2035 HDPUVs. The four-wheel drive coefficient is maintained at 500 (coefficient 'a') and the weighting multiplier coefficient is maintained at 0.75 (coefficient 'b').

Table 1-33: Characteristics of Alternative HDPUV10 – CI Vehicle Coefficients[82]

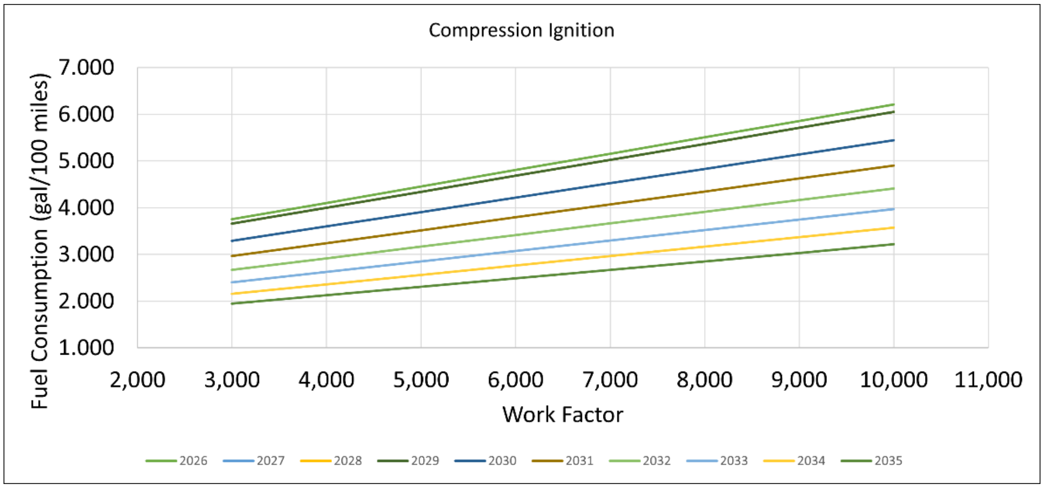
	2030	2031	2032	2033	2034	2035
e	0.00030762	0.00027686	0.00024917	0.00022425	0.00020183	0.00018165
f	2.370	2.133	1.919	1.728	1.555	1.399

Table 1-34: Characteristics of Alternative HDPUV10 – SI Vehicle Coefficients[83]

	2030	2031	2032	2033	2034	2035
c	0.00037368	0.00033631	0.00030268	0.00027241	0.00024517	0.00022065
d	2.876	2.589	2.330	2.097	1.887	1.698

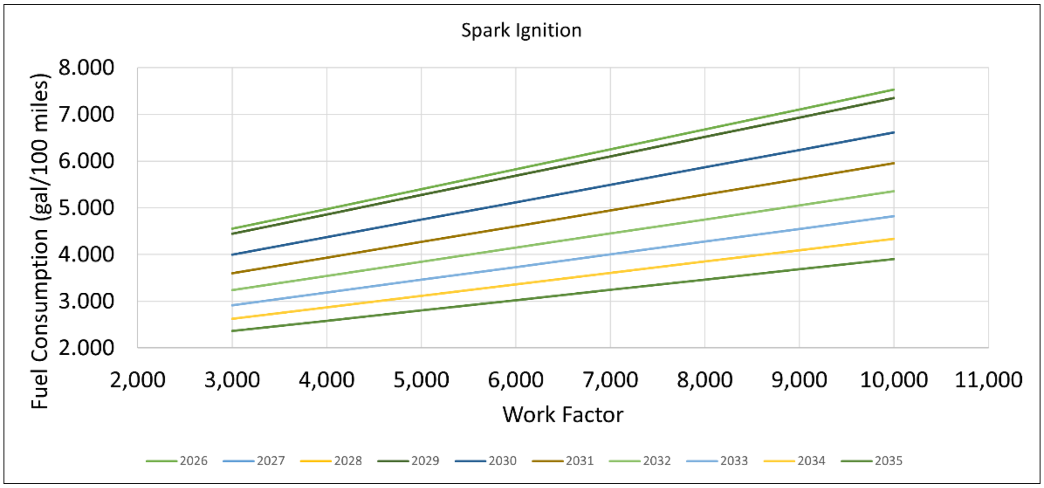
These equations are represented graphically below:

Figure 1-21: Alternative HDPUV10, HDPUV Fuel Efficiency – CI Vehicles, Target Curves



[82] In the CAFE Model, these are linear work-factor-based functions where coefficients e and f are for diesels, BEVs and FCEVs. See Equation 1-3 in Chapter 1.2.1.
[83] In the CAFE Model, these are linear work-factor-based functions where coefficients c and d are for gasoline, CNG, strong hybrid vehicles and PHEVs. See Equation 1-3 in Chapter 1.2.1.

Figure 1-22: Alternative HDPUV10, HDPUV Fuel Efficiency – SI Vehicles, Target Curves



1.4.3.9. Alternative HDPUV14

Alternative HDPUV14 would increase HDPUV standard stringency by 14 percent per year for model years 2030-2035 HDPUVs. The four-wheel drive coefficient is maintained at 500 (coefficient 'a') and the weighting multiplier coefficient is maintained at 0.75 (coefficient 'b').

Table 1-35: Characteristics of Alternative HDPUV14 – CI Vehicle Coefficients[84]

	2030	2031	2032	2033	2034	2035
e	0.00029395	0.00025280	0.00021740	0.00018697	0.00016079	0.00013828
f	2.264	1.947	1.675	1.440	1.239	1.065

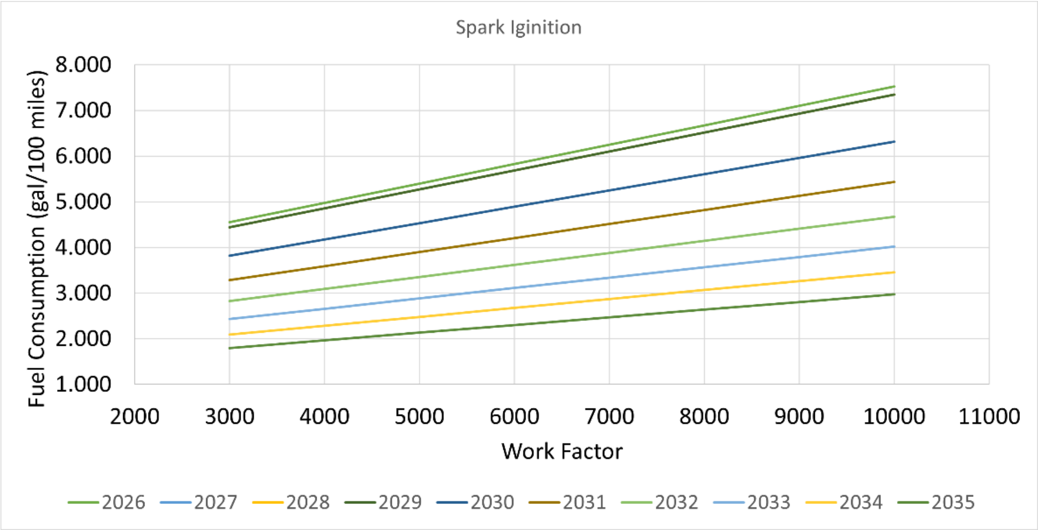
Table 1-36: Characteristics of Alternative HDPUV14 – SI Vehicle Coefficients[85]

	2030	2031	2032	2033	2034	2035
c	0.00035707	0.00030708	0.00026409	0.00022712	0.00019532	0.00016798
d	2.749	2.364	2.033	1.748	1.503	1.293

These equations are represented graphically below:

[84] In the CAFE Model, these are linear work-factor-based functions where coefficients e and f are for diesels, BEVs and FCEVs. See Equation 1-3 in Chapter 1.2.1.
[85] In the CAFE Model, these are linear work-factor-based functions where coefficients c and d are for gasoline, CNG, strong hybrid vehicles and PHEVs. See Equation 1-3 in Chapter 1.2.1.

Figure 1-23: Alternative HDPUV14, HDPUV Fuel Efficiency – SI Vehicles, Target Curves



2. What Inputs Does the Compliance Analysis Require?

CAFE Model Files Referenced in this Chapter

Below is a list of CAFE Model Files referenced in this chapter. See Chapter 2.1.9 "Where to Find the Internal NHTSA Files?" for a full list of files referenced in this document and their respective file locations.

- CAFE Model Documentation
- CAFE Model Input File
- Parameters Input File
- Technologies Input File
- Scenarios Input File
- CAFE Model Executable File
- Market Data Input File
- CAFE Analysis Autonomie Documentation
- Autonomie Input and Assumptions Description Files
- CAFE Model Output File
- Argonne National Laboratory Autonomie Results Dataset

The CAFE Model simulates the possible effects of standards on society. The model accomplishes this by simulating, first, the actions industry may take to comply with a set of standards, and second, simulating and calculating the resulting societal costs and benefits caused by those actions.

The CAFE Model applies various technologies to different vehicle models in each manufacturer's product line to simulate how each manufacturer might make progress toward compliance with the specified standard. Subject to a variety of user-controlled constraints, the CAFE Model applies technologies based on their relative cost-effectiveness, the cost of compliance, and the value of avoided fuel expenses. Cost-effectiveness is determined by several input assumptions regarding the cost and effectiveness of each technology. The cost of compliance is determined by the change in CAFE, CAFE-related civil penalties, or value of CO_2 credits, depending on the compliance program being evaluated. For a given manufacturer, the compliance simulation algorithm applies technologies either until the manufacturer runs out of cost-effective technologies, until the manufacturer exhausts all available technologies, or, if the manufacturer is assumed to be willing to pay civil penalties or acquire credits from another manufacturer (if applicable in a given scenario), until paying civil penalties or purchasing credits becomes more cost-effective than increasing vehicle fuel economy. Once complete, the simulation assigns an incurred technology cost and updated fuel economy to each vehicle model, as well as any civil penalties incurred by each manufacturer. This compliance simulation process is repeated for each model year of both the rulemaking time frame and study period. This analysis runs through model year 2050.

Once the compliance simulation is complete the CAFE Model transitions to effects calculations. At the conclusion of the compliance simulation for a given regulatory scenario, the model produces a full representation of the registered light-duty vehicle population in the United States for each model year and calendar year. The CAFE Model then uses this fleet to generate estimates of the following (for each model year and calendar year included in the analysis): lifetime travel, fuel consumption, carbon dioxide and criteria pollutant emissions, the magnitude of various economic externalities related to vehicular travel (e.g., congestion and noise), and energy consumption (e.g., the economic costs of short-term increases in petroleum prices, or social damages associated with GHG emissions). The model then uses these estimates to measure the benefits and costs associated with each regulatory alternative relative to a No-Action Alternative.

To perform this analysis, the CAFE Model uses millions of data points contained in several input files that have been populated by engineers, economists, and safety and environmental program analysts at both NHTSA and the DOT's Volpe National Transportations Systems Center (Volpe). In addition, some of the input data comes from modeling and simulation analysis performed by experts at ANL using their Autonomie full vehicle simulation model and BatPaC battery cost model.[86] Other inputs are derived from other models, such as the U.S. Energy Information Administration's (EIA's) NEMS, Argonne's "GREET" fuel-cycle emissions

[86] Argonne Natinoal Laboratory's report is titled "Vehicle Simulation Process to Support the Analysis for model year 2027 and Beyond CAFE and model year 2030 and Beyond HDPUV FE Standards" which for ease of use and consistency in the TSD document, it is being referred to as the "CAFE Analysis Autonomie Documentation".

analysis model, U.S. EPA's "MOVES" vehicle emissions analysis model, Ingenieurgesellschaft Auto und Verkehr's (IAV) engine models, and Southwest Research Institute's (SWRI) engine models.

Chapter 2 and Chapter 3 describe the inputs that the compliance simulation requires, including an in-depth discussion of the technologies used in the analysis, how they are defined in the CAFE Model, how they are characterized on vehicles that already exist in the market, how they can be applied to realistically simulate manufacturer's decisions, and their effectiveness and cost. The inputs and analyses for the effects calculations, including economic, safety, and environmental effects, are discussed later in Chapter 4 through Chapter 7, although the overview of inputs below provides a brief description of the information contained in the input files that supports those calculations. Throughout these chapters we will occasionally use DOT to refer to the collaborative work performed by both NHTSA and Volpe, because both organizations are part of the DOT.

2.1. Overview of Analysis Inputs and Assumptions

The CAFE Model input files used to define the analysis fleet,[87] the characteristics of the fuel-saving technologies considered in the analysis, safety considerations, and major economic factors. The input files contain about 150 thousand records and data points, all considered in the course of running the CAFE Model. The nature and function of many of these inputs remains mostly unchanged relative to previous versions of the CAFE Model, although DOT staff regularly updates the values of the inputs to represent the latest information available at the time of the rulemaking analysis.

The CAFE Model Documentation accompanying this final rule lists all the inputs, defines them, and describes how the inputs are used by the model.[88] However, this subsection provides an overview of the CAFE Model Input File, their general purpose and a brief description of the data they contain. Similar to the CAFE Model Documentation, this subsection is organized based on CAFE Model input types.

2.1.1. Technology Options and Pathways

We define the technology options available for the CAFE Model analysis and group those options into pathways. The pathways define relations of mutual exclusivity between conflicting sets of technologies. Additionally, each path designates the direction in which vehicles are allowed to advance as the modeling system evaluates specific technologies for application. Figure 2-1 shows the technology options and pathways used in the light-duty and HDPUV analyses.

[87] Discussed further below, the "analysis fleet" or "baseline fleet" (used interchangeably) located in the "Vehicles" worksheet of the Market Data Input File is our representation of the fleet of vehicles to which the CAFE Model adds technology; in some cases, this might be every vehicle model produced for sale in a specific model year, or it may be a combination of vehicle models produced in different MYs, depending on data avilability.
[88] CAFE Model Documentation.

Figure 2-1: CAFE Model Technology Pathways

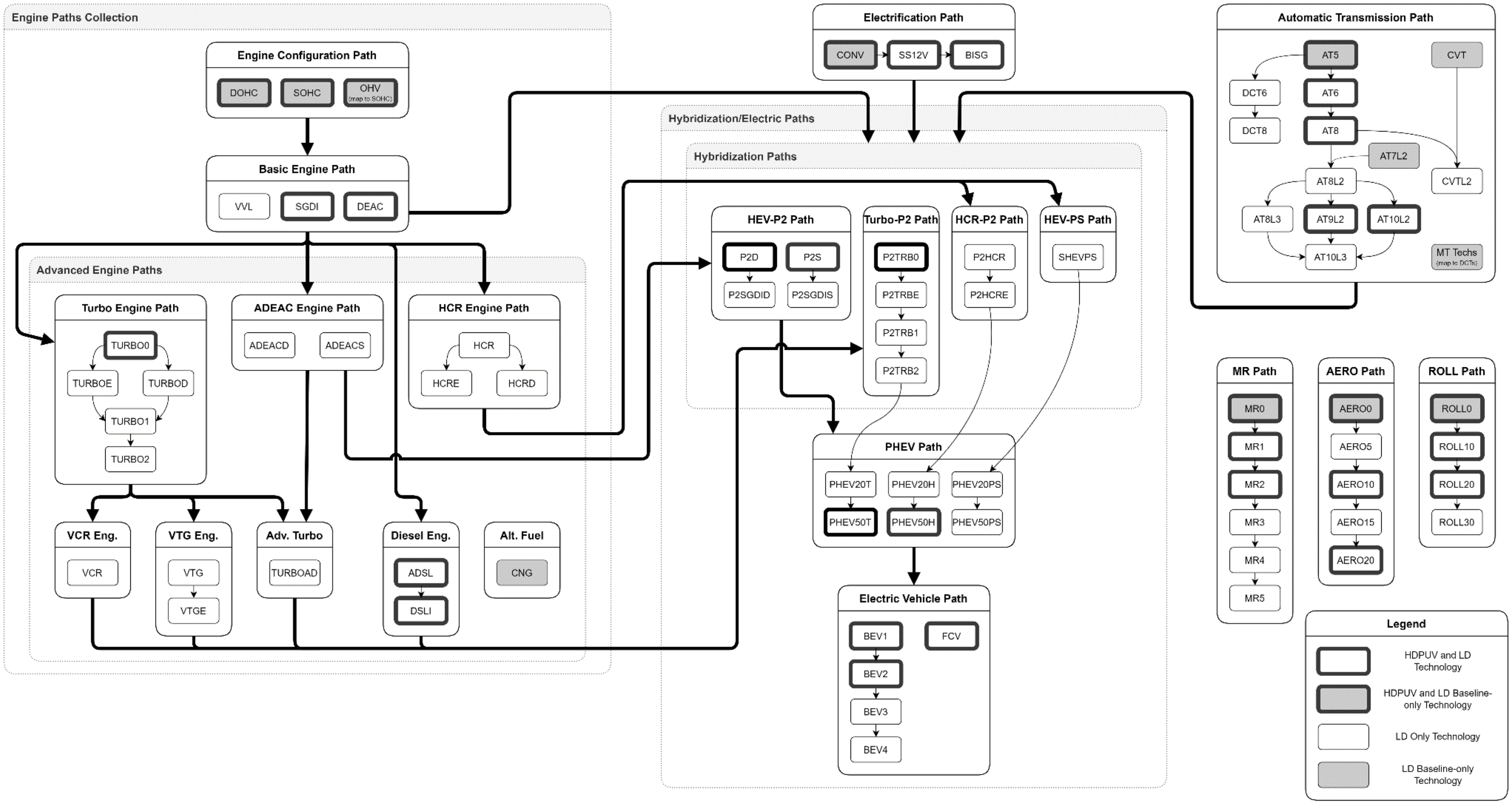


Table 2-1 and

Technology Name	Abbreviation	Technology Group
Single Overhead Camshaft Engine with VVT	SOHC	Basic Engines
Double Overhead Camshaft Engine with VVT	DOHC	Basic Engines
Variable Valve Lift	VVL	Basic Engines
Stoichiometric Gasoline Direct Injection	SGDI	Basic Engines
Cylinder Deactivation	DEAC	Basic Engines
Turbocharged Engine	TURBO0	Advanced Engines
Turbocharged Engine with Cooled Exhaust Gas Recirculation	TURBOE	Advanced Engines
Turbocharged Engine with Cylinder Deactivation	TURBOD	Advanced Engines
Advanced Turbocharged Engine, Level 1	TURBO1	Advanced Engines
Advanced Turbocharged Engine, Level 2	TURBO2	Advanced Engines
DOHC Engine with Advanced Cylinder Deactivation	ADEACD	Advanced Engines
SOHC Engine with Advanced Cylinder Deactivation	ADEACS	Advanced Engines
High Compression Ratio Engine	HCR	Advanced Engines
High Compression Ratio Engine with Cooled Exhaust Gas Recirculation	HCRE	Advanced Engines
High Compression Ratio Engine with Cylinder Deactivation	HCRD	Advanced Engines
Variable Compression Ratio Engine	VCR	Advanced Engines
Variable Turbo Geometry Engine	VTG	Advanced Engines
Variable Turbo Geometry Engine with eBooster	VTGE	Advanced Engines
Turbocharged Engine with Advanced Cylinder Deactivation	TURBOAD	Advanced Engines
Advanced Diesel Engine	ADSL	Advanced Engines
Advanced Diesel Engine with Improvements	DSLI	Advanced Engines
Compressed Natural Gas Engine	CNG	Advanced Engines
5-Speed Automatic Transmission	AT5	Transmissions
6-Speed Automatic Transmission	AT6	Transmissions
7-Speed Automatic Transmission with Level 2 high efficiency gearbox (HEG)	AT7L2	Transmissions
8-Speed Automatic Transmission	AT8	Transmissions
8-Speed Automatic Transmission with Level 2 HEG	AT8L2	Transmissions
8-Speed Automatic Transmission with Level 3 HEG	AT8L3	Transmissions
9-Speed Automatic Transmission with Level 2 HEG	AT9L2	Transmissions
10-Speed Automatic Transmission with Level 2 HEG	AT10L2	Transmissions
10-Speed Automatic Transmission with Level 3 HEG	AT10L3	Transmissions
6-Speed Dual Clutch Transmission	DCT6	Transmissions
8-Speed Dual Clutch Transmission	DCT8	Transmissions
Continuously Variable Transmission	CVT	Transmissions
Continuously Variable Transmission with Level 2 HEG	CVTL2	Transmissions
Conventional Powertrain (Non-Electric)	CONV	Electrification

12V Micro-Hybrid Start-Stop System	SS12V	Electrification
48V Belt Mounted Integrated Starter/Generator	BISG	Electrification
Parallel Strong Hybrid/Electric Vehicle with DOHC Engine	P2D	Electrification
Parallel Strong Hybrid/Electric Vehicle with DOHC+SGDI Engine	P2SGDID	Electrification
Parallel Strong Hybrid/Electric Vehicle with SOHC Engine	P2S	Electrification
Parallel Strong Hybrid/Electric Vehicle with SOHC+SGDI Engine	P2SGDIS	Electrification
Parallel Strong Hybrid Electric Vehicle with TURBO0 Engine	P2TRB0	Electrification
Parallel Strong Hybrid Electric Vehicle with TURBOE Engine	P2TRBE	Electrification
Parallel Strong Hybrid Electric Vehicle with TURBO1 Engine	P2TRB1	Electrification
Parallel Strong Hybrid Electric Vehicle with TURBO2 Engine	P2TRB2	Electrification
Parallel Strong Hybrid Electric Vehicle with HCR Engine	P2HCR	Electrification
Parallel Strong Hybrid Electric Vehicle with HCRE Engine	P2HCRE	Electrification
Power Split Strong Hybrid/Electric Vehicle with Full Time Atkinson Engine	SHEVPS	Electrification
Plug-in Hybrid Vehicle with TURBO1 Engine and 20 miles of electric range	PHEV20T	Electrification
Plug-in Hybrid Vehicle with TURBO1 Engine and 50 miles of electric range	PHEV50T	Electrification
Plug-in Hybrid Vehicle with HCR Engine and 20 miles of electric range	PHEV20H	Electrification
Plug-in Hybrid Vehicle with HCR Engine and 50 miles of electric range	PHEV50H	Electrification
Plug-in Hybrid Vehicle with Full Time Atkinson Engine and 20 miles of electric range	PHEV20PS	Electrification
Plug-in Hybrid Vehicle with Full Time Atkinson Engine and 50 miles of electric range	PHEV50PS	Electrification
Battery Electric Vehicle with 200 miles of range	BEV1	Electrification
Battery Electric Vehicle with 250 miles of range	BEV2	Electrification
Battery Electric Vehicle with 300 miles of range	BEV3	Electrification
Battery Electric Vehicle with 350 miles of range	BEV4	Electrification
Fuel Cell Electric Vehicle	FCEV	Electrification
Base Level Tire Rolling Resistance	ROLL0	Rolling Resistance
Tire Rolling Resistance, 10% Improvement	ROLL10	Rolling Resistance
Tire Rolling Resistance, 20% Improvement	ROLL20	Rolling Resistance
Tire Rolling Resistance, 30% Improvement	ROLL30	Rolling Resistance
Base Level Aerodynamic Drag Technology	AERO0	Aerodynamic Drag
Aerodynamic Drag, 5% Drag Coefficient Reduction	AERO5	Aerodynamic Drag
Aerodynamic Drag, 10% Drag Coefficient Reduction	AERO10	Aerodynamic Drag
Aerodynamic Drag, 15% Drag Coefficient Reduction	AERO15	Aerodynamic Drag
Aerodynamic Drag, 20% Drag Coefficient Reduction	AERO20	Aerodynamic Drag

Base Level Mass Reduction Technology	MR0	Mass Reduction
Mass Reduction – 5.0% of Glider	MR1	Mass Reduction
Mass Reduction – 7.5% of Glider	MR2	Mass Reduction
Mass Reduction – 10.0% of Glider	MR3	Mass Reduction
Mass Reduction – 15.0% of Glider	MR4	Mass Reduction
Mass Reduction – 20.0% of Glider	MR5	Mass Reduction

Table 2-2 list the technology options available for the light-duty and HDPUV analyses. The tables show each technology name, its abbreviation used in the analysis, and the technology group for each technology.

Table 2-1: Light-Duty Fleet Technologies

Technology Name	Abbreviation	Technology Group
Single Overhead Camshaft Engine with VVT	SOHC	Basic Engines
Double Overhead Camshaft Engine with VVT	DOHC	Basic Engines
Variable Valve Lift	VVL	Basic Engines
Stoichiometric Gasoline Direct Injection	SGDI	Basic Engines
Cylinder Deactivation	DEAC	Basic Engines
Turbocharged Engine	TURBO0	Advanced Engines
Turbocharged Engine with Cooled Exhaust Gas Recirculation	TURBOE	Advanced Engines
Turbocharged Engine with Cylinder Deactivation	TURBOD	Advanced Engines
Advanced Turbocharged Engine, Level 1	TURBO1	Advanced Engines
Advanced Turbocharged Engine, Level 2	TURBO2	Advanced Engines
DOHC Engine with Advanced Cylinder Deactivation	ADEACD	Advanced Engines
SOHC Engine with Advanced Cylinder Deactivation	ADEACS	Advanced Engines
High Compression Ratio Engine	HCR	Advanced Engines
High Compression Ratio Engine with Cooled Exhaust Gas Recirculation	HCRE	Advanced Engines
High Compression Ratio Engine with Cylinder Deactivation	HCRD	Advanced Engines
Variable Compression Ratio Engine	VCR	Advanced Engines
Variable Turbo Geometry Engine[89]	VTG	Advanced Engines
Variable Turbo Geometry Engine with eBooster	VTGE	Advanced Engines
Turbocharged Engine with Advanced Cylinder Deactivation	TURBOAD	Advanced Engines
Advanced Diesel Engine	ADSL	Advanced Engines
Advanced Diesel Engine with Improvements	DSLI	Advanced Engines
Compressed Natural Gas Engine	CNG	Advanced Engines
5-Speed Automatic Transmission	AT5	Transmissions
6-Speed Automatic Transmission	AT6	Transmissions
7-Speed Automatic Transmission with Level 2 high efficiency gearbox (HEG)	AT7L2	Transmissions
8-Speed Automatic Transmission	AT8	Transmissions

[89] Technology that enables Miller Cycle ICE.

8-Speed Automatic Transmission with Level 2 HEG	AT8L2	Transmissions
8-Speed Automatic Transmission with Level 3 HEG	AT8L3	Transmissions
9-Speed Automatic Transmission with Level 2 HEG	AT9L2	Transmissions
10-Speed Automatic Transmission with Level 2 HEG	AT10L2	Transmissions
10-Speed Automatic Transmission with Level 3 HEG	AT10L3	Transmissions
6-Speed Dual Clutch Transmission	DCT6	Transmissions
8-Speed Dual Clutch Transmission	DCT8	Transmissions
Continuously Variable Transmission[90]	CVT	Transmissions
Continuously Variable Transmission with Level 2 HEG[91]	CVTL2	Transmissions
Conventional Powertrain (Non-Electric)	CONV	Electrification
12V Micro-Hybrid Start-Stop System	SS12V	Electrification
48V Belt Mounted Integrated Starter/Generator	BISG	Electrification
Parallel Strong Hybrid/Electric Vehicle with DOHC Engine	P2D	Electrification
Parallel Strong Hybrid/Electric Vehicle with DOHC+SGDI Engine	P2SGDID	Electrification
Parallel Strong Hybrid/Electric Vehicle with SOHC Engine	P2S	Electrification
Parallel Strong Hybrid/Electric Vehicle with SOHC+SGDI Engine	P2SGDIS	Electrification
Parallel Strong Hybrid Electric Vehicle with TURBO0 Engine	P2TRB0	Electrification
Parallel Strong Hybrid Electric Vehicle with TURBOE Engine	P2TRBE	Electrification
Parallel Strong Hybrid Electric Vehicle with TURBO1 Engine	P2TRB1	Electrification
Parallel Strong Hybrid Electric Vehicle with TURBO2 Engine	P2TRB2	Electrification
Parallel Strong Hybrid Electric Vehicle with HCR Engine	P2HCR	Electrification
Parallel Strong Hybrid Electric Vehicle with HCRE Engine	P2HCRE	Electrification
Power Split Strong Hybrid/Electric Vehicle with Full Time Atkinson Engine	SHEVPS	Electrification
Plug-in Hybrid Vehicle with TURBO1 Engine and 20 miles of electric range	PHEV20T	Electrification
Plug-in Hybrid Vehicle with TURBO1 Engine and 50 miles of electric range	PHEV50T	Electrification
Plug-in Hybrid Vehicle with HCR Engine and 20 miles of electric range	PHEV20H	Electrification
Plug-in Hybrid Vehicle with HCR Engine and 50 miles of electric range	PHEV50H	Electrification
Plug-in Hybrid Vehicle with Full Time Atkinson Engine and 20 miles of electric range	PHEV20PS	Electrification
Plug-in Hybrid Vehicle with Full Time Atkinson Engine and 50 miles of electric range	PHEV50PS	Electrification
Battery Electric Vehicle with 200 miles of range	BEV1	Electrification
Battery Electric Vehicle with 250 miles of range	BEV2	Electrification

[90] Note that the CVT and CVTL2 technologies are not applicable to the Pickup and PickupHT technology classes.
[91] Note that the CVT and CVTL2 technologies are not applicable to the Pickup and PickupHT technology classes.

Battery Electric Vehicle with 300 miles of range	BEV3	Electrification
Battery Electric Vehicle with 350 miles of range	BEV4	Electrification
Fuel Cell Electric Vehicle	FCEV	Electrification
Base Level Tire Rolling Resistance	ROLL0	Rolling Resistance
Tire Rolling Resistance, 10% Improvement	ROLL10	Rolling Resistance
Tire Rolling Resistance, 20% Improvement	ROLL20	Rolling Resistance
Tire Rolling Resistance, 30% Improvement	ROLL30	Rolling Resistance
Base Level Aerodynamic Drag Technology	AERO0	Aerodynamic Drag
Aerodynamic Drag, 5% Drag Coefficient Reduction	AERO5	Aerodynamic Drag
Aerodynamic Drag, 10% Drag Coefficient Reduction	AERO10	Aerodynamic Drag
Aerodynamic Drag, 15% Drag Coefficient Reduction	AERO15	Aerodynamic Drag
Aerodynamic Drag, 20% Drag Coefficient Reduction	AERO20	Aerodynamic Drag
Base Level Mass Reduction Technology	MR0	Mass Reduction
Mass Reduction – 5.0% of Glider	MR1	Mass Reduction
Mass Reduction – 7.5% of Glider	MR2	Mass Reduction
Mass Reduction – 10.0% of Glider	MR3	Mass Reduction
Mass Reduction – 15.0% of Glider	MR4	Mass Reduction
Mass Reduction – 20.0% of Glider	MR5	Mass Reduction

Table 2-2: Heavy-Duty Pickup Truck and Van Technologies

Technology Name	Abbreviation	Technology Group
Single Overhead Camshaft Engine with VVT	SOHC	Basic Engines
Double Overhead Camshaft Engine with VVT	DOHC	Basic Engines
Stoichiometric Gasoline Direct Injection	SGDI	Basic Engines
Cylinder Deactivation	DEAC	Basic Engines
Turbocharged Engine	TURBO0	Advanced Engines
Advanced Diesel Engine	ADSL	Advanced Engines
Advanced Diesel Engine with Improvements	DSLI	Advanced Engines
5-Speed Automatic Transmission	AT5	Transmissions
6-Speed Automatic Transmission	AT6	Transmissions
8-Speed Automatic Transmission	AT8	Transmissions
9-Speed Automatic Transmission with Level 2 HEG	AT9L2	Transmissions
10-Speed Automatic Transmission with Level 2 HEG	AT10L2	Transmissions
Conventional Powertrain (Non-Electric)	CONV	Electrification
12V Micro-Hybrid Start-Stop System	SS12V	Electrification
Belt Mounted Integrated Starter/Generator	BISG	Electrification

Parallel Strong Hybrid/Electric Vehicle with SOHC Engine[92,93]	P2S (*P2D, P2TRB0*)	Electrification
Plug-in Hybrid Vehicle with SOHC Engine and 50 miles of electric range[94,95]	PHEV50H (*PHEV50T*)	Electrification
Battery Electric Vehicle with 150 miles of range (for van classes) or 200 miles of range (for pickup classes)	BEV1	Electrification
Battery Electric Vehicle with 250 miles of range (for van classes) or 300 miles of range (for pickup classes)	BEV2	Electrification
Fuel Cell Electric Vehicle	FCEV	Electrification
Base Level Tire Rolling Resistance	ROLL0	Rolling Resistance
Tire Rolling Resistance, 10% Improvement	ROLL10	Rolling Resistance
Tire Rolling Resistance, 20% Improvement	ROLL20	Rolling Resistance
Base Level Aerodynamic Drag Technology	AERO0	Aerodynamic Drag
Aerodynamic Drag, 10% Drag Coefficient Reduction	AERO10	Aerodynamic Drag
Aerodynamic Drag, 20% Drag Coefficient Reduction	AERO20	Aerodynamic Drag
Base Level Mass Reduction Technology	MR0	Mass Reduction
Mass Reduction – 1.4% of Glider	MR1	Mass Reduction
Mass Reduction – 13.0% of Glider	MR2	Mass Reduction

2.1.2. Market Data Input File

The Market Data Input File contains the detailed description of the vehicle model and model configurations each manufacturer produces for sale in the United States. The file also contains a range of other inputs that are not specific to individual vehicle models but are specific to individual manufacturers.

The file contains a set of worksheets, as follows:

- **"Manufacturers" worksheet:** Lists specific manufacturers, indicates whether manufacturers are expected to prefer paying CAFE fines to applying technologies that would not be cost-effective, indicates what "payback period" defines buyers' willingness to pay for fuel economy improvements, enumerates CAFE and CO_2 credits banked from model years prior to those represented explicitly, indicates amounts of each manufacturer's production that are relevant to compliance with ZEV programs, and indicates how sales "multipliers" are to be applied when simulating compliance with CO_2 standards.
- **"Credits and Adjustments" worksheet:** Enumerates estimates—specific to each manufacturer and fleet—of expected CO_2 and CAFE adjustments reflecting improved AC efficiency, reduced AC leakage, off cycle technologies, and production of flexible fuel vehicles (FFVs). The model applies AC leakage adjustments only to CO_2 levels and applies FFV adjustments only to CAFE levels. The AC leakage, AC efficiency, and off-cycle adjustment values in this worksheet are the achievable values we've estimated for each manufacturer, as discussed in Chapter 3.7 and presented in Table 3-127 and Table 3-128. These adjustment values have not been subjected to their applicable caps; the adjustment caps, which are discussed in Chapter 3.7.1, are maintained in the Scenarios Input File.[96]

[92] The P2S, P2D, and P2TRB0 technologies listed in Table 2-2 are all representation of the same "Parallel Strong Hybrid/Electric Vehicle with SOHC Engine" (P2S) technology. The P2S technology was originally simulated by Argonne using the Autonomie model. However, due to limitations of the CAFE Model version used for this analysis (with respect to technology pathway traversal), DOT staff created duplicates of P2S and copied its effectiveness and cost into the P2D and P2TRB0 nodes.
[93] The transmission used for HDPUV P2 HEVs would be equivalent to an AT8L2 even though that technology is not available to be selected by the model.
[94] The PHEV50H and PHEV50T technologies listed in Table 2-2 are both representation of the same "Plug-in Hybrid Vehicle with SOHC Engine and 50 miles of electric range" (PHEV50H) technology. As with the P2S technology, PHEV50H was originally simulated by Argonne; however, due to the current CAFE Model limitations, DOT staff duplicated PHEV50H into the PHEV50T node.
[95] The transmission used for HDPUV PHEVs would be equivalent to an AT8L2 even though that technology is not available to be selected by the model.
[96] For more discussion on how the CAFE Model incorporates AC leakage, AC efficiency, and off-cycle technologies into its compliance modeling, see Chapter Two S5.4 of the CAFE Model Documentation.

- **"Vehicles" worksheet:** Lists vehicle models and model configurations each manufacturer produces for sale in the United States; indicates which platform, engine, and transmission is present in each vehicle platform configuration; specifies each vehicle platform configuration's fuel economy level, production volume, and average price; specifies several engineering characteristics (e.g., curb weight, footprint, and fuel tank volume); assigns each vehicle platform configuration to a regulatory class, technology class, engine class, and safety class; indicates which platforms might reasonably be treated as candidates to be replaced with vehicles earning credit toward compliance with ZEV programs; specifies schedules on which specific vehicle models are expected to be redesigned and freshened; specifies how much U.S. labor is involved in producing each vehicle model/configuration; and indicates whether specific technologies are already present on specific vehicle model configurations, or, due to engineering or product planning considerations, should be skipped. DOT staff have updated this worksheet with additional inputs pertaining to compliance with ZEV programs, specifying the earliest model year when a vehicle may become a ZEV, and a "reference vehicle" that may be used as the source for shifting production volumes into a ZEV candidate, as further discussed in Chapter 2.5.1, Simulating the ZEV Programs.
- **"Platforms" worksheet:** Identifies specific platforms used by each manufacturer and for each platform, lists a unique code (referenced by the platform code specified for each vehicle model configuration), specifies the name of the platform, indicates optional platform-specific redesign and refresh schedules, and indicates whether specific technologies are already present on specific platforms, or, due to engineering or product planning considerations, should be skipped. For this final rule, DOT staff have added the Platforms worksheet to the Market Data Input File to discretely represent each platform's configuration and to better account for the vehicle models that use that platform.
- **"Engines" worksheet:** Similar to the Platforms worksheet, identifies specific engines used by each manufacturer and for each engine, lists a unique code (referenced by the engine code specified for each vehicle model configuration), identifies the fuel(s) with which the engine is compatible, specifies the valvetrain design (e.g., dual overhead cam [DOHC]), specifies the engine's displacement, cylinder configuration and count, identifies the engine's aspiration type (e.g., naturally aspirated, turbocharged), and indicates whether specific technologies are already present on specific engines, or, due to engineering or product planning considerations, should be skipped. DOT staff have updated this worksheet to include optional engine-specific redesign and refresh schedules.
- **"Transmissions" worksheet:** Similar to the Platforms and Engines worksheet, identifies specific transmissions used by each manufacturer and for each transmission, lists a unique code (referenced by the transmission code specified for each vehicle model configuration), identifies the type (e.g., automatic or continuously variable transmission (CVT)), specifies the number of forward gears, and indicates whether specific technologies are already present, or, due to engineering or product planning considerations, should be skipped. As with the Engines worksheet, DOT staff have updated this worksheet to include optional transmission-specific redesign and refresh schedules.

2.1.3. Technologies Input File

The Technologies Input File identifies approximately six dozen technologies to be included in the analysis, indicates when and how widely each technology can be applied to specific types of vehicles, provides most of the inputs involved in estimating what costs will be incurred, and provides some of the inputs involved in estimating impacts on vehicle fuel consumption and weight.

The file contains the following types of worksheets:

- **"Parameters" worksheet:** Not to be confused with the Parameters Input File discussed below, this worksheet in the Technologies Input File indicates, for each technology class, the share of the vehicle's curb weight represented by the "glider" (the vehicle without the powertrain).
- **"Technologies" worksheet:** For each named technology, specifies the share of the entire fleet to which the technology may be additionally applied in each model year and indicates the amount of ZEV credits that may be earned from application of specific technologies.
- **"Technology Class" worksheets:** In a separate worksheet for each of the 14 technology classes (discussed below), identifies whether and how soon the technology is expected to be available for wide commercialization, specifies the percentage of miles a vehicle is expected to travel on a secondary fuel (if

applicable, as for PHEVs), indicates a vehicle's expected electric power and all-electric range (AER) (if applicable), specifies expected impacts on vehicle weight, specifies estimates of costs for technologies in each model year (and factors by which electric battery costs are expected to be reduced in each model year), specifies any estimates of maintenance and repair cost impacts, and specifies any estimates of consumers' willingness to pay for the technology.

- **"Engine Technology Class" worksheets:** In a separate worksheet for each of the 52 initial engine types identified by cylinder count, number of cylinder banks, and configuration (DOHC, unless identified as OHV or single overhead cam [SOHC]), specifies estimates of costs in each model year, as well as any estimates of impacts on maintenance and repair costs.

2.1.4. Parameters Input File

The Parameters Input File contains inputs spanning a range of considerations, such as economic and labor utilization impacts, vehicle fleet characteristics, fuel prices, scrappage and safety model coefficients, fuel properties, and emission rates.

The file contains a set of specific worksheets, as follows:

- **"Economic Values" worksheet:** Specifies a variety of inputs, including social and consumer discount rates to be applied, the "base year" to which to discount social benefits and costs (i.e., the reference years for present value analysis), discount rates to be applied to the Social Cost of CO_2 emissions, the elasticity of highway travel with respect to per-mile fuel costs (also referred to as the rebound effect), the gap between test (for certification) and on-road (i.e., real world) fuel economy, the fixed amount of time involved in each refuel event, the share of the tank refueled during an average refueling event, the value of travel time (in dollars per hour per vehicle), the estimated average number of miles between mid-trip EV recharging events (separately for each BEV considered in the analysis), the rate (in miles of capacity per hour of charging) at which EV batteries are recharged during such events, the values (in dollars per vehicle mile) of congestion and noise costs, costs of vehicle ownership and operation (e.g., sales tax), economic costs of oil imports, estimates of future macroeconomic measures (e.g., GDP), and rates of growth in overall highway travel (separately for low, reference, and high oil prices).
- **"Vehicle Age Data" worksheet:** Specifies nominal average survival rates and annual mileage accumulation for cars, vans and SUVs, pickup trucks, and heavy-duty pickup trucks and vans. These inputs are used only for displaying estimates of avoided fuel savings and CO_2 emissions while the model is operating. Calculations reported in the CAFE Model output files reflect, among other things, application of the scrappage model.
- **"Fuel Prices" worksheet:** Separately for gasoline, E85, diesel, electricity, hydrogen, and compressed natural gas (CNG), specifies historical and estimated future fuel prices (and average rates of taxation).
- **"Dynamic Fleet Share (DFS) Model Values" worksheet:** Specifies coefficients used by the dynamic fleet share model, which estimates the relative proportions of passengers and light trucks in the total U.S. market for new vehicles. This page also includes an annual forecast of passenger car share used if the static fleet share option is selected.
- **"Sales Model Values" worksheet:** Specifies coefficients applied by the nominal sales forecast model, which the CAFE Model uses to estimate the number of Light-Duty Vehicles (LDVs) sold in each model year of the analysis period. Also contains an annual forecasted level of sales by class which the CAFE Model uses to estimate the number of HDPUVs sold in each model year of the analysis.
- **"Scrappage Model Values" worksheet:** Specifies coefficients applied by the scrappage model, which the CAFE Model uses to estimate rates at which vehicles will be scrapped (removed from service) during the period covered by the analysis.
- **"Historic Fleet Data" worksheet:** For model years not simulated explicitly (here, model years through 2021), and separately for cars, vans and SUVs, pickup trucks, and HDPUVs, specifies the initial size (i.e., number new vehicles produced for sale in the United States) of the fleet, the number still in service in the indicated calendar year (here, 2021), the relative shares of different fuel types, and the average fuel economy achieved by vehicles with different fuel types, and the averages of horsepower (HP), curb weight, fuel capacity, and price (when new).

- **"Safety Values" worksheet:** Specifies coefficients used to estimate the extent to which changes in vehicle mass impact highway safety. Also, specifies the values assigned to preventing highway fatalities, nonfatal injuries, and property damaged vehicles, as well as the share of incremental risk (of any additional driving) internalized by drivers and the base year for annual growth. Chapter 7 discusses these estimation procedures.
- **"Fatality Rates (FR)" worksheet:** Separately for each model year from 1975-2050 and vehicle age (through a maximum of 39 years), specifies the estimated number of fatalities, non-fatal injuries, and vehicles sustaining property damage in crashes per billion miles of travel. Vehicles produced during each model year reach a unique age in each subsequent calendar year; for example, those produced during model year 2020 are defined to have age=0 in calendar year 2020, and to have reached age=10 in calendar year 2030.
- **"Credit Trading Values" worksheet:** Specifies whether various provisions related to compliance credits are to be simulated (currently limited to credit carry-forward and transfers) and specifies the maximum number of years' credits may be carried forward to future model years. Also, specifies statutory (for CAFE only) limits on the quantity of credits that may be transferred between fleets, and specifies amounts of lifetime mileage accumulation to be assumed when adjusting the value of transferred credits. Also, accommodates a setting indicating the maximum number of model years to consider when using expiring credits.
- **"ZEV Credit Values" worksheet:** Specifies the percentage requirements of states' zero-emission vehicle programs (ACC I and II and ACT) by model year. Also includes PHEV cap where applicable.
- **"Employment Values" worksheet:** Specifies the estimated average revenue original equipment manufacturers (OEMs) and suppliers earn per employee, the RPE factor applied in developing technology costs, the average quantity of annual labor (in hours) per employee, a multiplier to apply to U.S. final assembly labor utilization in order to obtain estimated direct automotive manufacturing labor, and a multiplier to be applied to all labor hours.
- **"Fuel Properties" worksheet:** Separately for gasoline, E85, diesel, electricity, hydrogen, and CNG, specifies energy density, mass density, carbon content, and vehicle-based SO_2 emissions (grams per unit of energy).
- **"Fuel Import Assumptions" worksheet:** Separately for gasoline, E85, diesel, electricity, hydrogen, and CNG, specifies the extent to which (a) changes in fuel consumption lead to changes in net imports of finished fuel, (b) changes in fuel consumption lead to changes in domestic refining output, (c) changes in domestic refining output lead to changes in domestic crude oil production, and (d) changes in domestic refining output lead to changes in net imports of crude oil.
- **"Emissions Health Impacts" worksheet:** Separately for NO_X, SO_2 and $PM_{2.5}$ emissions, separately for upstream and vehicular emissions, and for each of calendar years 2020, 2025, and 2030, specifies estimates of various health impacts, such as premature deaths, acute bronchitis, and respiratory hospital admissions. Consulting with technical staff at EPA and ANL, DOT staff have refined the structure of these inputs to account separately for refining, petroleum extraction, finished fuel distribution (i.e., transportation, storage, and distribution), and electricity generation, and to differentiate between gasoline and diesel, light-duty and heavy-duty vehicle emissions.
- **"Greenhouse Emission Costs" worksheet:** For each calendar year through 2080, specifies four different estimates of the social cost of CO_2 emissions, in dollars per metric ton. Accommodates analogous estimates for methane (CH_4) and N_2O.
- **"Criteria Pollutant Emission Costs" worksheet:** Separately for NO_X, SO_2 and $PM_{2.5}$ emissions, separately for upstream and vehicular emissions, and for each of calendar years 2020, 2025, and 2030, specifies social costs on a per-ton basis.
- **"Upstream Emissions (UE)" worksheets:** Separately for gasoline, E85, diesel, electricity, hydrogen, and CNG, and separately for calendar years 2020, 2025, 2030, 2035, 2040, 2045, and 2050, and separately for various upstream processes (e.g., petroleum refining), specifies emission factors (in grams per million British thermal unit [BTU]) for each included criteria pollutant (e.g., NO_X) and toxic air contaminant (e.g., benzene).
- **"Tailpipe Emissions (TE)" worksheets:** Separately for gasoline and diesel, for each of model years 1975-2050, for each vehicle vintage through age 39, specifies vehicle-based emission factors (in grams

per mile) for CO, volatile organic compounds (VOC), NO_X, $PM_{2.5}$, CH_4, N_2O, acetaldehyde, acrolein, benzene, butadiene, formaldehyde, and diesel particulate matter (PM) 10 microns or less in diameter (PM_{10}).

- **"BTW Emissions" worksheet:** Specifies BTW emission rates across fuels, separately for gasoline, E85, diesel, electricity, hydrogen, and CNG and by vehicle class.

2.1.5. Scenarios Input File

The CAFE Model represents each regulatory alternative as a discrete scenario, identifying the first-listed scenario as the reference point relative to which impacts are calculated. Each scenario is described in a worksheet in the Scenarios Input File, with standards and related provisions specified separately for each regulatory class (which are identified in the input file as "Passenger Car," "Light Truck," or "HDPUV") and each model year. Inputs specify the standards' functional forms and define coefficients in each model year, separately for the CAFE and CO_2 compliance programs. For functional forms not native to the CO_2 program, multiplicative factors and additive offsets may be used to convert fuel economy targets to CO_2 targets, the two being directly mathematically related by a linear transformation. Additional inputs specify minimum CAFE standards for domestic passenger car fleets; determine whether upstream emissions from electricity and hydrogen are to be included in CO_2 compliance calculations; identify specific model years for which new standards are being finalized; specify the governing rates for CAFE civil penalties; identify how FFVs and PHEVs are to be accounted for in CAFE compliance calculations; define unit costs and caps on credits generated from AC leakage, AC efficiency, and off-cycle technologies;[97] and specify any estimated amounts of average tax credits earned by HEVs, PHEVs, BEVs, and FCVs. DOT staff have updated this worksheet to accommodate discrete inputs for the PEF applicable to PHEVs and BEVs. Additionally, tax credit provisions have been extended to include a scaling factor on the credit amount, as well as to account for the tax credits attributed to the suppliers of HEV batteries.

2.1.6. Runtime Settings

In addition to inputs contained in the above-mentioned files, the CAFE Model makes use of additional settings selected when operating the model. These include which compliance program (CAFE, CO_2, or both) is to be evaluated; the range of model years to evaluate for analysis; the initial model year when technology application begins; the model years during which technology application and vehicle sales under each regulatory alternative remain unchanged from the No-Action Alternative (i.e., the reference baseline); whether the use of compliance credits is to be simulated; the assumed amount of accumulated driving (in miles) to use when estimating impacts on new vehicle sales and used vehicle scrappage; whether low, average, or high estimates are to be applied for fatality rates; the amount by which to scale benefits to consumers; and whether to calculate and report an implicit opportunity cost. Further settings include the ability to enable the dynamic economic models, along with various accompanying configuration options that specify the number of sales model iterations to be undertaken, the price elasticity multiplier, which dynamic fleet share models to use, and whether fleet shares from the No-Action Alternative are applied to each regulatory alternative. For this analysis, DOT staff have introduced new settings to the model, supporting a selection of a dynamically computed or a user-defined sales forecast for the No-Action Alternative, and supporting the ability to adjust fleet shares from the No-Action Alternative prior to applying them in the regulatory alternatives.

2.1.7. Simulation Inputs

As mentioned above, the CAFE Model makes use of databases of estimates of fuel consumption impacts and, as applicable, battery costs for different combinations of fuel saving technologies. For this analysis, DOT developed these databases using a large set of full vehicles and accompanying battery cost model simulations developed by ANL. To ensure accuracy of the input data and maintain computational efficiency, DOT has integrated the databases into the CAFE Model Executable File. When the model is run, the databases are processed and loaded into memory for analysis. However, the CAFE Model also provides a menu option to extract the databases and place them in an accessible location on the user's disk drive.

[97] See Chapter 3.7 for additional details on how the CAFE Model simulates AC leakage, AC efficiency, and off-cycle technologies.

The extracted databases, each of which is in the form of a simple (if somewhat large) text file, are as follows:

- **"FE1_Adjustments.csv":** Defines the main database of fuel consumption improvement estimates. Each record contains such estimates for a specific indexed combination of technologies (using a multidimensional "key") for each of the technology classes in the Market Data and Technologies Input Files. Each estimate is specified as a percentage of the "base" technology combination for the indicated technology class.
- **"FE2_Adjustments.csv":** Specific to PHEVs, defines a database of fuel consumption improvement estimates applicable to operation on electricity, specified in the same manner as those in the main database.
- **"Battery_Costs.csv":** Specific to technology combinations involving vehicle electrification, defines a database of estimates of corresponding BatPaC-based base year battery costs (before learning effects) for batteries in these systems.

2.1.8. Autonomie Vehicle Simulation Databases

As discussed above, the technology effectiveness values used in the CAFE Model come from a set of full vehicle simulations developed by ANL using the Autonomie model. While DOT adapts these prohibitively large simulation databases into the CAFE Model Executable File, DOT provides a summary of simulation outputs for each vehicle technology class. Argonne also provides Autonomie Input and Assumptions Descriptions Files to describe the assumptions used in building vehicle models and for the BatPaC battery cost modeling.

For the light-duty fleet, the workbooks Argonne[98] provides for the full vehicle simulations are, as follows:

- **"CompactNonPerfo_2206.csv; CompactPerfo_2206.csv; MidsizeNonPerfo_2206.csv; MidsizePerfo_2206.csv; MidsizeSUVNonPerfo_2206.csv; MidsizeSUVPerfo_2206.csv; PickupNonPerfo_2206.csv; PickupPerfo_2206.csv; SmallSUVNonPerfo_2206.csv; SmallSUVPerfo_2206.csv**": These are the ten databases that contain the outputs of the Autonomie full vehicle simulations for the light-duty vehicle fleet. These ten vehicle classes account for approximately 150 thousand simulations (in each vehicle class) that have been considered for this analysis. These results are in raw absolute mpg form, which are then converted to the appropriate incremental effectiveness value for use in the CAFE Model.[99]
- **"ANL - All Assumptions_Summary_NPRM_2206.xlsx":** This summary workbook provides broad summaries of assumptions used for the Autonomie full vehicle simulations, such as component weights, cold start penalties, component specifications, etc.
- **"ANL - Data Dictionary_NPRM_2206.xlsx":** This workbook contains descriptions of inputs and units for the Autonomie simulation results.
- **"ANL - Summary of Main Component Performance Assumptions_NPRM_2206.xlsx":** This workbook contains another set of characteristics data for transmission efficiencies, engine fueling rates, and electric motor (EM) efficiencies. It also contains the inputs, assumptions, and outputs of the battery pack modeling performed by Argonne for this analysis.

For the HDPUV fleet, the workbooks Argonne provides for the full vehicle simulations are, as follows:

- "**C2P_Processed_220811.csv; C2V_Processed_220811.csv; C3P_Processed_220811.csv; C3V_Processed_220811.csv**": These are the four databases that contain the outputs of the Autonomie full vehicle simulations for the HDPUV fleet, and account for approximately 2,500 full vehicle simulations considered in this analysis. As with the light-duty vehicle simulations, the HDPUV results are specified in raw absolute mpg form and are converted accordingly prior to use with the CAFE Model.

[98] For the final rule analysis, we used the same NPRM Autonomie full vehicle simualtions hence the file names that are indiciated_NPRM.
[99] It is important to note that while absolute fuel economy values are calculated by the Autonomie model, the CAFE Model only uses the relative fuel economy values to determine the effectiveness of any given technology key.

- **"ANL - All Assumptions Summary - (2b-3) FY22 NHTSA - 220811.xlsx":** This summary workbook provides broad summaries of assumptions used for the Autonomie full vehicle simulations, such as component weights, cold start penalties, component specifications, etc.
- **"ANL - Data Dictionary - (2b-3) FY22 NHTSA - 2200811.xlsx":** This workbook contains descriptions of inputs and units for the Autonomie simulation results.
- **"ANL - Summary of Main Component Performance Assumptions - (2b-3) FY22 NHTSA - 220811.xlsx":** This workbook contains another set of characteristics data for transmission efficiencies, engine fueling rates, and EM efficiencies. It also contains the inputs, assumptions, and outputs of the battery pack modeling performed by Argonne for this analysis.

2.1.9. Where to Find the Internal NHTSA Files?

As in the past, for the purpose of transparency and easier review of the files used for this analysis we post our CAFE Model source code, inputs, and outputs on our website. This is located on https://www.nhtsa.gov/laws-regulations/corporate-average-fuel-economy.[100]

Below is a table of all CAFE Model Files referenced in this TSD and their respective file locations. See the text box at the beginning of each chapter to find all CAFE Model Files referenced in that particular chapter.

Table 2-3: Internal NHTSA Files

NHTSA Internal File	File Location
CAFE Model Documentation	NHTSA CAFE Model Website > Downloads > CAFE Model Documentation
CAFE Model Input File	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > Central Analysis Zip > input
Market Data Input File	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > Central Analysis Zip > input > market_data_ref.xlsx
Parameters Input File	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > Central Analysis Zip > input > parameters_ref.xlsx
Technologies Input File	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > Central Analysis Zip > input > technologies_ref.xlsx
tran.f NEMS Source File	EIA Website > Annual Energy Outlook > Information on Obtaining NEMS > NEMS Archive zip file > reference > source > tran.f
Scenarios Input File	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > Central Analysis Zip > input > scenarios_ref.xlsx
SS CAFE Model Scenarios Input File (standard settings)	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > Central Analysis Zip > input > scenarios_ref.xlsx
EIS CAFE Model Scenarios Input File (environmental impact statement mode)	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > Central Analysis Zip > input > scenarios_eis.xlsx
CAFE Model Output File	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > Central Analysis Zip > output
Vehicle Report Output File	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > Central Analysis Zip > output > ref > reports-csv > vehicles_report.xlsx
CAFE Model Compliance Output File	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > Central Analysis Zip > output > ref > reports-csv > compliance_report.xlsx
CAFE Model Executable File	

[100] See NHTSA. 2023. Corporate Average Fuel Economy. Available at: https://www.nhtsa.gov/laws-regulations/corporate-average-fuel-economy.

CAFE Model Program Directory	NHTSA CAFE Model Website > Downloads > Model Software > CAFE Model (installed directory)
CAFE Model Battery Costs File	
CAFE Model Fuel Economy Adjustment Files	
CAFE Analysis Autonomie Documentation	Docket > Browse Documents > Argonne Autonomie Inputs and Documents (Supporting and Related Material)
Argonne National Laboratory Autonomie Results Dataset	
Autonomie Input and Assumptions Description Files	
Argonne National Laboratory Autonomie Results Data Dictionary	
BatPaC Assumptions Tab in the BatPaC Lookup Tables	
BatPaC Lookup Tables	
Argonne National Laboratory Autonomie Results Dataset	
BenMAP Health Incidence Files	Docket > Browse Documents > EPA Reports
BenMAP EC/OC Health Incidence Files	

2.2. The Market Data Input File

The starting point for the evaluation of different stringency levels for future fuel economy standards is the analysis fleet, which is a snapshot of the recent light-duty or HDPUV vehicle markets. For this analysis two analysis fleets were constructed, a light-duty fleet that represents the model year 2022 fleet of light-duty vehicles sold, and the HDPUV fleet that represents a composite fleet of vehicles sold in recent model years. Each analysis fleet provides a reference point to project how manufacturers could apply additional technologies to vehicles to cost-effectively improve vehicle fuel economy, in response to regulatory action and market conditions.[101] As the scope of CAFE analysis has widened over successive rulemakings, the range of data that must be included for each vehicle in the analysis fleet has, in turn, widened, currently including nearly half a million pieces of information used and referenced in the CAFE Model analysis.

The Market Data Input File contains information about manufacturer credit banks, fine payment preferences, and whether a manufacturer has voluntarily adopted the California Framework Agreements, in which they committed to exceed standards set in the 2020 final rule. Additionally, the Market Data Input File includes some information about the distribution of vehicle sales within the United States, recognizing the proportion of vehicles sold in California and Section 177 states, and in the rest of the United States. This information supports the representation of ZEV programs and manufacturer commitments congruent with potential future ZEV program levels, discussed in detail below. Credit banks, fine payment preferences, and other information described in this paragraph appear on the "Manufacturers" tab of the Market Data Input File.

The "Credits and Adjustments" tab of the Market Data Input File summarizes additional credits previously claimed by manufacturer, by regulatory class. On this tab, the Market Data Input File includes historical data about claimed AC efficiency, AC leakage, OC improvement values, and FFV credits, as well as forward looking projections about AC and OC improvement values that DOT believes may be claimed in the future.

[101] The CAFE Model does not generate compliance paths a manufacturer should, must, or will deploy. It is intended as a tool to demonstrate a compliance pathway a manufacturer *could* choose. It is almost certain all manufacturers will make compliance choices differing from those projected by the CAFE Model.

The "Vehicles" tab of the Market Data Input File includes information about the vehicles sold in the United States in a given model year. In this tab, DOT staff catalogue the types of vehicles sold, the number sold, the regulatory class, the footprint, the fuel economy, and other information about those vehicles that informs the initial starting point for the analysis. Of particular importance is an assessment of which fuel saving technologies already appear on the vehicles. The vehicles tab includes information necessary to link observed vehicles to effectiveness estimates for additional fuel saving technologies and technology costs, by linking each vehicle to a vehicle technology class, engine class, or platform. The Market Data Input File contains additional information about projected refresh and redesign cycles, and current part sharing of structural parts, engines, and transmissions. These factors are all taken into account by the CAFE Model when applying additional fuel saving technologies. Estimates of manufacturer suggested retail price (MSRP), labor hours per vehicle, and percent U.S. content provide reference information used in CAFE Model effects calculations.

The Market Data Input File "Platforms," "Engines," and "Transmissions" tabs characterize technology content of vehicle platforms, as well as engine and transmission systems in use in the observed fleet and link these systems back to observed vehicles via the "platform code," "engine code," and "transmission code."

A reasonable characterization of the analysis fleet is key to estimating costs and benefits resulting from the rulemaking action. The analysis fleet sales volumes, fuel economies, and manufacturer fleet fuel economies act as the starting place for the CAFE Model compliance simulations that evaluate how manufacturers may respond to any projected future standards. The analysis fleet inputs, as characterized in the Market Data Input File, also provide a technology starting point for the CAFE Model when the compliance model begins consideration of what technologies may be adopted in the future, based on redesign cycle and parts sharing. The definition of this technology starting point is important because it reduces the likelihood of "double-counting" the effectiveness of technologies, which can occur if the analysis assumes already applied technologies are still available to improve a vehicle's fuel economy. The analysis fleet also accounts for the idea that some fuel saving technologies may not meet functional requirements for all vehicle types, or performance applications. The Market Data Input File, and information outlined in this TSD, endeavors to make clear the initial assumptions with respect to the analysis fleet used in a rulemaking analysis.

The market for automotive equipment in the United States is highly heterogeneous, and even half a million data points may not be enough to characterize every potentially relevant nuance of the automotive marketplace. As with every fuel economy rulemaking, this analysis fleets reflect a balance between the exigencies of the rulemaking and the availability of supporting data.

The following subchapters discuss the inputs included in the Market Data Input File for the light-duty and HDPUV analyses, including vehicles and their technology content (i.e., the analysis fleet), and other starting points for safety, economic, and manufacturer compliance positions.

2.2.1. Characterizing Vehicles and Their Technology Content

Most of the information in the Market Data Input File is about specific vehicles, including sales, fuel economies, regulatory class, and the vehicle specifications. The input file is based on best information available at the time DOT staff assemble the Market Data Input File. Beyond specifications, information in the Market Data Input File links parts of the analysis. For instance, while the analysis fleet captures the starting point for fuel saving technology content already in use, by vehicle, the Market Data Input File also includes information linking individual vehicles to technology effectiveness estimates and technology costs. These values may vary by the type of vehicle, and the configuration of equipment on the vehicle.

In the Market Data Input File, DOT staff assign each vehicle a "technology class." The technology class is used to link the observed vehicle to effectiveness estimates and technology costs. The CAFE Model references the ANL Autonomie simulations for many effectiveness estimates used in the compliance simulation. In these simulations, Argonne projects the fuel economies for ten different types of light-duty vehicles and four different types of HDPUVs, for many combinations of fuel saving technologies. The technology class in the Market Data Input File points the CAFE Model to the most relevant reference set of effectiveness estimates for each vehicle. Similarly, some costs for fuel saving technologies vary by the type of vehicle. The technology class in the Market Data Input File also points the CAFE Model to the most relevant reference costs in the "Technologies Input File," with costs for vehicle technologies being listed on the associated technology class tab.

Just as some vehicle technology costs vary by type of vehicle (or technology class, as listed in the Market Data and Technologies Input Files), the cost of fuel saving engine technologies and some electrification systems vary by the engine architecture, or peak power output most closely associated with an engine architecture. For instance, the cost of adding dynamic cylinder deactivation (DEAC) to a naturally aspirated DOHC inline four-cylinder engine is not projected to be the same as adding DEAC to a naturally aspirated overhead valve (OHV) V eight-cylinder engine. Similarly, some naturally aspirated inline four-cylinder engines may retain four cylinders when turbocharged ("4C1B" engine technology class, meaning an engine with four cylinders and one bank), but lower power variants might go to three cylinders when turbocharged ("4C1B_L" engine technology class), and thereby have lower projected costs in comparison for the step to turbocharging. For a more detailed discussion of the mechanics of engine technology classes, naming conventions, and engine costs, see Chapter 3.1. The engine technology class in the Market Data Input File points the CAFE Model to the most relevant engine technology costs.

For each configuration of a vehicle, referred to as a row, the Market Data Input File lists a certification fuel economy, sales volume, regulatory class, and footprint. These are the bare minimum pieces of information needed to understand if a manufacturer is under or over complying with standards. The Market Data Input File often includes a few rows for vehicles that may have identical certification fuel economies, regulatory classes, and footprints (with compliance sales volumes divided out among rows), because other pieces of information used in the CAFE Model may be dissimilar.

For instance, for a given nameplate, the curb weight may vary by trim level, with premium trim levels often weighing more on account of additional equipment on the vehicle; or, a manufacturer may provide consumers the option to purchase a larger fuel tank size for their vehicle. These pieces of information may not impact the observed compliance position directly, but curb weight, in relation to other vehicle attributes, is important to assess mass reduction (MR) technology already used on the vehicle, and fuel tank size is directly relevant to saving time at the gas pump, which the CAFE Model uses when calculating the value of avoided time spent refueling.

The Market Data Input File also provides an inventory of fuel saving technologies already equipped on the observed vehicles. A reasonable characterization is important: underestimating the amount of fuel saving technology content on a vehicle would allow the CAFE Model to apply that technology again in the compliance simulation and create a "phantom" projection of potential fuel economy savings. In contrast, overestimating the amount of fuel saving technology content already on a vehicle would also remove the misapplied technologies from consideration, and confuse the cost accounting if that technology is replaced with another. For example, if the assigned amount of engine technology content is higher than actually used, the projected incremental cost to switch to electrified technologies may be underestimated, because the cost of removed technologies will be overestimated. The initial analysis fleet assignment process for each technology is described in detail in Chapter 3.

For some fuel saving technologies, manufacturers share parts or systems to get the most from economies of scale. The CAFE Model accounts for some relationships between vehicles that are important to consider. For instance, similar engines and transmissions often appear on many types of vehicles. Manufacturers often use platforms (with shared MR technologies) on a family of vehicles. The CAFE Model includes measures to maintain complexity in compliance simulations as it evaluates cost-effective compliance pathways. DOT staff assign each vehicle in the Market Data Input File a "platform code," an "engine code," and a "transmission code." With few exceptions, vehicles that share engines codes, and thus engines, will adopt engine technologies together, while vehicles that share transmissions will adopt them together.[102] Likewise, vehicles that share platforms will adopt MR technologies together. Redesign cycles for all of the vehicles that share components may not always be in sync; as a result, vehicles with shared components and laggard redesigns and refreshes will inherit shared technologies at the first available opportunity.

[102] One exception to sharing is between light-duty and HDPUV fleets; even though some engines, transmissions, or platforms might be shared, the underlying Autonomie simulations are different thus sharing was severed.

In limited cases, the Market Data Input File includes information about technologies that the CAFE Model may *not* apply. For the row on the vehicle, platform, engine, or transmission tabs, and for the associated technology column listed on those tabs, "SKIP" appears in the spreadsheet cell for any technology that is not applicable to vehicle or component of a given row. Generally, the logic for applying these skips is derived from engineering data and stakeholder provided information. Examples of SKIP logic includes SKIPs to high levels of aerodynamic improvements that need to take into account form drag for some vehicle body styles, SKIPs to high levels of rolling resistance for performance vehicles that have high needs for traction to meet handling objectives, and SKIPs to some engine packages to account for low specific power output and torque requirements. If SKIP is applicable for a technology, the rules for restricting technology for a specific set of vehicles are described in Chapter 3. High-level considerations for technology applicability determinations are discussed further in Chapter 2.6.

The CAFE Model considers many types of fuel saving technologies, but some are very difficult to observe from public information available. For instance, the rolling resistance of a set of tires may not appear on a public specifications sheet, and the inner workings and efficiencies of a transmission may be hard for DOT staff to assess without detailed study, or CBI. In these cases, DOT staff rely on best information available, and, occasionally, analyst or engineering judgement, or described analytical techniques, like in the case of MR technology. When manufacturers or suppliers do provide CBI, we often verify the information in due time, usually through contracted analysis at independent labs. We often try to gather multiple sources of information to support each data point.

For this analysis, when assembling the light-duty vehicle fleet, for some technologies, such as rolling resistance and aerodynamic improvements, DOT staff relied on confidential information provided by manufacturers about their model year 2016 light-duty fleet, and carried these values forward, by nameplate, for the model year 2022 fleet. With this approach, it is possible that DOT underestimates the extent to which manufacturers have added harder-to-observe technologies in the model year 2022 fleet since model year 2016, increasing the risk of "double counting" effectiveness, especially for aerodynamics, and rolling resistance. While some technologies are difficult to observe, many other technologies are straightforward to identify via specification sheets, marketing materials, or published technical papers. These technologies can be directly linked with the most representative Argonne simulation, and technology cost estimate. Whether a technology is easy to observe, or difficult to observe, DOT staff assign technology content for each vehicle in the analysis fleet in the Market Data Input File.

The Market Data Input Files catalogue DOT's understanding of technologies already equipped on vehicles, with many vehicles not yet exhausting all technologies that may improve internal combustion engine (ICE) efficiency. The current technology assessment in the analysis fleet shows that many vehicles, even ones with advanced engine or transmission technologies, still may be marginally improved with the application of additional technologies. Often, recently released engines or transmissions may be reasonably characterized as early adopters of some technologies already considered in the analysis, in combination with a representation of a previous generation, widely adopted technology.

The following subchapters discuss the data sources used to populate the analysis fleets, and how DOT staff accurately characterize the starting point for the compliance simulation.

2.2.1.1. Data Sources Used to Populate the Analysis Fleet

The Market Data Input File integrates information from many sources, including manufacturer compliance submissions, publicly available information, and CBI. At times, information is still incomplete, and DOT staff use analyst judgement to complete populating the analysis fleet. When analyst judgement is used, DOT staff try to make clear the underlying data and logic informing the analysis. Forward looking refresh/redesign cycles are one example of when analyst judgement is necessary.

DOT staff make every effort to use current, credible sources with information that may be shared with the public or independently verified. For the light-duty fleet, DOT staff used pre-model year 2022 compliance data as the basis of the analysis fleet.[103] Due to different reporting requirements for HDPUV fleet, DOT staff relied on compliance data from model years ranging between model year 2014 and model year 2022.[104] For light-duty vehicles, compliance data contains information about projected sales volumes, vehicle fuel economies, vehicle footprints, and often contains some information about engine architecture, transmission architecture, and vehicle drive configuration. For HDPUV vehicles, compliance data similarly contains sales volumes, fuel consumption values, vehicle work factors, engine displacement, fuel type, axle ratios, body configurations, and some other relevant information for identifying the vehicles.[105] For each vehicle nameplate, DOT staff identified and downloaded manufacturer specification sheets, usually from the manufacturer media website, or from online marketing brochures.[106] From specification sheets, DOT staff gathered information to identify engine technologies, engine families, transmission technologies, transmission families, and electrified drivetrain technologies. We also recorded curb weights (often varying by powertrain, by drive configuration, and by trim level), peak HP, and occasionally a manufacturer reported vehicle's aerodynamic drag coefficient. For additional information about how specification sheets informed the assignment of a technology to a vehicle in the model year 2022 fleet, see the technology specific "analysis fleet assignment" subchapters in Chapter 3.

Often, one entry in the compliance record (typically including a nameplate, sales volume, fuel economy, footprint, drive configuration, and basic description of the engine and transmission) describes a range of vehicles with attributes that may vary meaningfully for the CAFE Model analysis. For instance, one compliance record may represent a range of trim levels, offered for sale at a range of prices, or spanning a range of curb weights. In most of these cases, DOT staff averaged the MSRP and curb weights of the multiple trims that would match the row presented in the compliance record.

One consequence of using historical compliance data to populate the Market Data Input File is that the analysis carries forward fleet composition, or at least iterates the fleet from an observation taken in the past. In other words, the Market Data Input File does not use forward looking information to project which nameplates may be introduced, or which nameplates will be retired, or evaluate how competitive positions may evolve as manufacturers add fuel saving technologies and adjust product plans over time.[107,108] Similarly, manufacturers who submitted no compliance information in the compliance year for which we pulled analysis fleet data (perhaps because they had not yet commercialized products), are not included in the forward looking compliance simulation. The Market Data Input File does identify some vehicle models/configurations for which each manufacturer may adopt ZEV candidate technology (in this case, BEV technology), and more detail about how DOT staff selected these vehicles is described in Chapter 2.5.1.2, Calculation of ZEV Credit Targets per Manufacturer. As a result, it is reasonable to expect the composition of the fleet (in terms of nameplates offered, and manufacturer market shares) to look very different in the future years beyond the rulemaking time frame than the CAFE Model's projected compliance pathways.

2.2.1.1.1. Source and Vintage of Fleet Data

Using recent data for analysis fleet assessments is more likely to reflect current market conditions than older data. Recent data will inherently include manufacturer's practical considerations about fuel saving technology characterization and efficiency, mix shifts in response to consumer preferences, and industry sales volumes that incorporate substantive macroeconomic events. Also, using recent data decreases the likelihood that the

[103] Pre-model year compliance data comprises of manufacturer's predictions of the volume of vehicles they will be producing in the upcoming model year. There is a high probability that these numbers will differ from the actual production volumes for that model year.

[104] The compliance data used as the basis of the HDPUV fleet differed by manufacturer as follows: pre-model year 2014 for Mercedes-Benz, final model year 2018 for Ford and GM, final model year 2019 for Stellantis, and final model year 2020 for Nissan. The specifications for these vehicles in the Market Data Input File match the vintage of compliance data. Vehicles that were observed to have been redesigned since the compliance year were given redesigns in 2023.

[105] For this final rule, vehicles were divided between light-duty and HDPUV based on manufacturer's compliance filings which differs from the NPRM in which GVWR was used solely to assign vehicles to each fleet.

[106] The catalogue of reference specification sheets (broken down by manufacturer, by nameplate) used to populate information in the Market Data Input File is available on NHTSA's website. BMW Data, FCA Data, Ford Data, Hyundai Data, Kia Data, Mercedes Data, Nissan Data, Toyota Data, Volvo Data, GM Data, Honda Data, Mitsubishi Data, VW Data, and Jaguar Land Rover (JLR) Data.

[107] The sales model in the CAFE Model does, at an industry level, adjust overall sales volume up or down, and sales share between LTs and passenger cars in response to technology costs, fuel economies, and fuel prices.

[108] DOT staff understand that nameplates are often retired. Rows in the Market Data Input File should be considered proxies for vehicles in a specific category for a specific manufacturer. In most instances, a manufacturer will maintain their position in that category with a new vehicle in the future which will be represented by that retired nameplate.

CAFE Model selects compliance pathways for future standards that affect vehicles already built in previous model years.[109]

While current data are highly desirable, real-time data to support fleet characterization in the Market Data Input File are extremely difficult to come by. There is a lag time for finalized model year compliance data and finalized compliance data for a given model year may not be available for a year or more after the last product for that model year rolls off the assembly line. Further complicating matters, once DOT staff identify a suitable set of compliance data, it takes significant effort to translate those compliance data into the Market Data Input File, augment that information with data from specification sheets and CBI, characterize fuel saving technology content on each vehicle, and produce a high-quality file that is suitable for use in the CAFE Model. DOT must balance the resources required to create the Market Data Input File (i.e., several staff for several months), with the availability of data and the timing of the rulemaking effort.

As noted above, for this analysis, DOT staff used pre-model year compliance submissions from model year 2022 for the light-duty fleet, and varying compliance submissions for model years ranging between 2014-2022 for the HDPUV fleet, to serve as the basis for the analysis fleet characterized in the Market Data Input File. While the data used for this analysis is not the "final" data for model year 2022, the compliance submissions and sales projections used therein provide the most up to date information available at the time the Market Data Input File was assembled. Since the CAFE Model must project any missing years between the analysis starting year (i.e., model year 2022) and the initial alternative scenario analysis year (i.e., model year 2027 for light-duty, or model year 2030 for HDPUV), relying on newer information (even if preliminary) is likely to improve the overall accuracy of compliance simulations.[110]

Upon assembly of the model year 2022 Market Data Input File, on occasion the DOT staff had to disaggregate compliance data to capture variation in curb weights, manufacturer suggested retail prices, and other market data fields that varied by trim level. As a result, the specific trim level sales volumes are estimates that reflect a mostly even distribution of sales volume as reported at the compliance level across sub-divisions. However, the combined compliance level reporting data are still reflected, exactly, in the Market Data Input File, when the atomized rows are aggregated. With respect to the luxury option content, and sales volumes of an individual trim level (to the extent that the Market Data Input File row volume reflects a disaggregated compliance row), the Market Data Input File can only go so far. However, the rows (and vehicle characteristics recorded) are well suited for use in the CAFE Model for projecting compliance pathways in response to regulatory alternatives.

2.2.1.1.2. Treatment of Confidential Business Information in Fleet Development

Some data in the Market Data Input File are informed by confidential business information (CBI). For instance, some pre-model year manufacturer compliance submissions are marked as confidential. DOT staff occasionally considers CBI to assess vehicle engineering characteristics that, like rolling resistance and aerodynamic drag, are neither included in compliance data nor reliably available.

Prior to the 2018 NPRM, DOT staff gave manufacturers the opportunity to confidentially share rolling resistance values and drag coefficients. Manufacturers had commented extensively, in response to the Draft Technical Assessment Report (TAR), that their prior efforts to improve aerodynamics and tire rolling resistance (ROLL) had not been reasonably characterized in the Draft TAR Market Data Input File. Many manufacturers volunteered engineering data (aerodynamic drag coefficients, and ROLL values) to inform DOT staff, resulting in a more informed characterization of fuel saving technology already equipped on vehicles, and a more informed mapping of observed vehicles onto reference Argonne simulations and projected technology costs. However, this took place in 2017. The Market Data Input File for this analysis

[109] For example, in this analysis the CAFE Model must apply technology to the model year 2022 fleet from MYs 2023-2026 for the compliance simulation that begins in model year 2027 (for the light-duty fleet), and from MYs 2023-2029 for the compliance simulation that begins in model year 2030. While manufacturers have already built model year 2022 and later vehicles, the most current, complete dataset with regulatory fuel economy test results to build the analysis fleet at the time of writing remains model year 2022 data for the light-duty fleet, and a range of MYs between 2014 and 2022 for the HDPUV fleet.

[110] In the case of the HDPUV fleet, for some manufacturers recent compliance submissions were not made available for use by DOT staff. Since the HDPUV vehicle fleet is considerably smaller than the light-duty fleet, omitting manufacturers for which no recent data exists may adversely affect compliance simulation within the CAFE Model, as well as produce an incomplete picture of the overall industry's compliance posture. As such, in the cases where no new data were available, DOT staff have decided to rely on manufacturer's older compliance information.

still, in many cases, references previously submitted CBI, even though manufacturers may have integrated additional rolling resistance and aerodynamic technology over the past few years. DOT staff have supplemented the older CBI with recent studies and public information, when more recent, credible, information is available, such as data from published specification sheets. Generally, DOT recognizes benefits from referencing recent, credible information to inform the characterization of vehicles in the Market Data Input File and the analysis fleet.

In addition, some transmission content, accessory efficiency improvements, and other vehicle technologies are difficult for DOT staff to objectively verify. As a practical matter, DOT cannot do a teardown study of every vehicle in the fleet every time staff produce a new analysis fleet. Agency staff use engineering judgement, and occasionally rely upon supplier, manufacturer, and Argonne's Advanced Mobility Technology Laboratory (AMTL) presented information to inform the Market Data Input File.

2.2.1.2. Technology Classes in the Fleet

The Market Data Input File includes information the CAFE Model uses to connect each observed vehicle with estimates of the effectiveness of other possible combinations of fuel saving technologies and estimated costs of those technologies. The "technology class" assigned in the Market Data Input File is the link the CAFE Model uses and is based on compliance data and DOT staff characterization of vehicle attributes.

During the compliance simulations, the CAFE Model evaluates adding fuel saving technologies to each vehicle appearing in the Market Data Input File, at some level of projected fuel economy benefit. The CAFE Model references incremental effectiveness estimates to project how the fuel efficiency of a vehicle may improve with the additional fuel saving technologies. For the CAFE Model to select the most relevant reference effectiveness estimate, from a catalogue of approximately 150 thousand Autonomie simulations, the Market Data Input File defines a "type," or technology class, for each vehicle. The Market Data Input File also defines the combination of fuel saving technologies already applied to that vehicle, or technology key, as the technologies listed as "USED" on the vehicles, platforms, engines, and transmissions tabs of the Market Data Input File. With this information, the CAFE Model identifies the reference point, along with the effectiveness and cost estimates, for the vehicles as they progress through the compliance simulations.

The CAFE Model considers costs of additional fuel saving technologies when forecasting which technologies manufacturers are likely to adopt in future scenarios. Technology costs can vary by vehicle type. The Technologies Input File lists the technology costs, with the CAFE Model using the technology class and engine technology class information from the Market Data Input File to lookup the appropriate costs for each vehicle and fuel saving technology. The CAFE Model also references battery costs for electrification technologies, with base year battery costs being derived from Argonne's BatPaC Model and Autonomie simulations. These costs often vary significantly by technology class and by combination of road load reducing technologies.

As noted in Chapter 2.1.3, the Technologies Input File lists fourteen technology classes that are supported by the CAFE Model. Of those, ten are designated for the light-duty fleet, while the remaining four are applicable to the HDPUV fleet. The assignment of a technology class to each vehicle model is discussed in the following two subchapters.

2.2.1.2.1. Light-Duty Classes

The CAFE Model defines ten technology classes for use by the light-duty fleet: SmallCar, MedCar, SmallSUV, MedSUV, Pickup, SmallCarPerf, MedCarPerf, SmallSUVPerf, MedSUVPerf, and heavy-duty pickup truck (PickupHT). The algorithm by which each vehicle model/configuration is assigned to one of these technology classes is a two-step process. First, a "size" of a technology class is assigned to each nameplate; only the SmallCar, MedCar, SmallSUV, MedSUV, and Pickup classes are eligible to be assigned in this step. The algorithm then evaluates whether to assign the performance variant of the initial assignment to each vehicle within the nameplate. Performance variants include the SmallCarPerf, MedCarPerf, SmallSUVPerf, MedSUVPerf, and PickupHT classes.

The evaluations in both steps of the algorithm are conducted quantitatively using "fit scores," which are calculations that consider key characteristics of vehicles in the fleet and compare those to the characteristics of each technology class.[111] A vehicle receives a fit score for every technology class for which it is eligible. The lower the fit score, the more closely aligned a vehicle's characteristics are with the characteristics for a given technology class. Therefore, the algorithm will assign the technology class with the lowest fit score to a given vehicle.

In the first step of the algorithm, the fit score used to assign the "size" of a technology class evaluates each vehicle's footprint and curb weight according to Equation 2-1. The difference in curb weight between the vehicle and the class reference weight is divided by a "pounds per 1 second" quantity[112] that normalizes the equation such that curb weight and footprint are more equally weighted. Note that the equation is also weighted by the ratio of individual vehicle sales to total sales for the nameplate, so that the initial assignment favors higher-selling vehicle models. The MR0 curb weight is calculated as part of the MR level assignment process.[113]

Equation 2-1: Size Fit Score

$$\text{Size Fit Score} = \frac{\textit{Vehicle Sales}}{\textit{Nameplate Sales}^{114}} \times \sqrt{\left(\frac{\textit{MR0 Curb Weight}}{\textit{Pounds per 1 second}} - \frac{\textit{Class Baseline Curb Weight}}{\textit{Pounds per 1 second}}\right)^2 + (\textit{Vehicle footprint} - \textit{Class Average Footprint})^2}$$

In the second step, the fit score that evaluates the performance variant of the technology class, as seen in Equation 2-2, takes a 0 to 60 miles per hour (mph) acceleration time into account.

Equation 2-2: Performance Fit Score

$$\textit{Performance Fit Score} = |(\textit{Vehicle estimated 0 to 60 time}) - (\textit{Class Baseline 0 to 60 time})|$$

This characteristic is not consistently reported in publicly available data, so a 0 to 60 mph acceleration time for each vehicle is estimated based on its weight-to-HP ratio, as calculated in Equation 2-3.

Equation 2-3: Vehicle Estimated 0 to 60 mph Acceleration Time

$$\textit{Vehicle estimated 0 to 60 time} = \left(\frac{\textit{Vehicle curb weight } [kg]}{\textit{Vehicle power } [kW]} \times 0.5991\right) + 1.8514$$

The Pickup and PickupHT classes are evaluated slightly differently. They use a different fit score calculation that considers the same vehicle characteristics as Equation 2-1, Equation 2-2, and Equation 2-3. The first step of the algorithm will initially assign the Pickup class if a vehicle has been assigned the "pickup" body style. The second step then assigns a fit score to Pickup and PickupHT that takes into account footprint, curb weight, and a 0 to 60 mph acceleration time, as seen in Equation 2-4.

[111] Baseline 0 to 60 mph acceleration times are assumed for each technology class as part of the full vehicle simulations conducted in Autonomie. For more information, see Chapter 2.3 Technology Effectiveness Values. DOT staff calculated class baseline curb weights and footprints by averaging the curb weights and footprints of vehicles within each technology class as assigned in previous analyses.

[112] This quantity is calculated by multiplying the vehicle's HP by 2.744 due to unit coversion for the fit which is calculated on kW/kg basis rather than using lbs and hp as the Market Data Input File does, additional details on the fit curve development are in Draft TAR 5-328, available at https://www.nhtsa.gov/sites/nhtsa.gov/files/draft-tar-final.pdf. For example, a vehicle with 200 hp would have a value of roughly 548.8 lbs per 1 second. A 200 lb weight difference between MR0 curb weight and class baseline would have a value of 0.36 instead of 200. This allows us to compare to the delta in footprint without orders of magnitude difference between the two which would completely cancel out the effects of one.

[113] For more information on how MR0 curb weight is calculated, see Chapter 3.4.2 Mass Reduction Analysis Light-Duty Fleet Assignments.

[114] In previous rulemakings, each row was treated individually and some instances of vehicles having different size technology classes would happen (some variants might be MedSUV and other SmallSUVPerf). All of the rows for a nameplate now receive the same size tech class assignment and to do so the fit scores of each row are sales weighted so that the overall fit for a nameplate is dependent on the bulk of the vehicle sales.

Equation 2-4: Pickup Fit Score

$$\text{Pickup Fit Score} = \sqrt{\left(\frac{MR0\ Curb\ Weight}{Pounds\ per\ 1\ second} - \frac{Class\ Baseline\ Curb\ Weight}{Pounds\ per\ 1\ second}\right)^2 + (Vehicle\ footprint\text{-}Class\ Average\ Footprint)^2 + (Vehicle\ estimated\ 0\ to\ 60\ mph\ acceleration\ time\text{-}Class\ Baseline\ 0\ to\ 60\ mph\ acceleration\ time)^2}$$

2.2.1.2.2. Medium Duty Classes

The CAFE Model defines four technology classes for the HDPUV fleet: Pickup2b, Van2b, Pickup3, and Van3. The algorithm for assigning a technology class for each HDPUV model/configuration differs from what was used for the light-duty fleet and is predominantly based on the classification and body style of the vehicle. That is, “class 2b” vehicles (with GVWR between 8,501 and 10,000 lbs.) are initially assigned to the Pickup2b or Van2b technology class, while “class 3” vehicles (GVWR between 10,001 and 14,000 lbs.) are initially assigned to the Pickup3 and Van3 classes. From here, fleet SUVs, work trucks, and chassis cab trucks are assigned to one of the “pickup” classes, while work vans, cutaways, and chassis cab vans are assigned to one of the “van” technology classes.[115]

2.2.1.3. Fuel Saving Technology Content

The CAFE Model considers the application of many technologies to improve vehicle fuel economy. For each of these technologies, on each vehicle application, the CAFE Model needs the reference cost and effectiveness values. The CAFE Model must also consider which technologies are already equipped on vehicles in the analysis fleet, information that is specified in the Market Data Input File. If a technology is included in the analysis for possible application, that technology appears in the heading row of the Market Data Input File, either on the vehicles, platforms, engines, or transmissions tabs. The analysis fleet identifies which combination of modeled technologies most reasonably represents the fuel saving technologies on each vehicle in the compliance data. If a technology is present in a vehicle the term “USED” will appear in the vehicles row, under the column with the technology named in the heading.

Many of the technologies in the CAFE Model may be applied in combination. For instance, an engine and transmission may be selected independent of one another, and road load reducing technologies (MR, aerodynamic drag, and rolling resistance) may be applied in any combination. Basic engine technologies (defined in Chapter 3.1) may be applied in any combination. In the effectiveness estimates, some technologies have synergies, while others offer efficiency improvements from the same mechanism,[116] and therefore provide less benefit in combination than the sum of their efficiency improvements generated independently.

Some technologies cannot appear together on one vehicle (defined as a single row in the Market Data Input File) in the analysis. For instance, a vehicle may only have one advanced engine at a time. Similarly, BEVs combine a fixed drive gear box with the EM and do not have an ICE or a conventional transmission.[117]

The following two subchapters provide a listing of technologies supported by the CAFE Model, along with their locations within the Market Data Input File. For additional information on the characterization of these technologies including their cost, prevalence in the model year 2022 fleet, effectiveness estimates, and considerations for their adoption, see the appropriate technology subchapters in Chapter 3 for more information.

2.2.1.3.1. Light-Duty Vehicles

The products offered in the U.S. light-duty automotive marketplace are highly heterogeneous, and manufacturers routinely update their products. Over time, some innovation efforts and investments in

[115] The following were reassigned to the light-duty fleet for this rule: all Rivian vehicles, Ford F150 Lightnings, and some Ford Transits Wagons.
[116] For example, SHEVP2 paired with advanced engine technologies. See Chapter 3.1.1 for further discussion.
[117] See Chapter 3.3.3 for additional discusion on the battery electric vehicle adoption features and cost considerations.

research and development can pay off, and manufacturers may bring to market new fuel saving technologies. The CAFE Model considers many technologies; some are nearly universally adopted in the model year 2022 fleet, some are used occasionally but show great future potential, and others have yet to be commercialized but are reasonable to include in the analysis based on reported activities in the supply chain and manufacturer interest. Similarly, costs of technologies in the future may be uncertain, but the analysis inputs assume that innovations will occur to lower the costs of many fuel saving technologies over time. As manufacturers and suppliers bring technologies to market, intellectual property can significantly influence which manufacturers adopt technologies, and at what cost. While every application of technology may have its own nuance, the CAFE Model effectiveness and cost assumptions attempt to represent a general characterization of fuel saving technologies that is a reasonable representation of the technology for any manufacturer.

The fuel saving technologies considered in this analysis for the light-duty fleet are listed in Table 2-4.

Table 2-4: Fuel Saving Technologies that the CAFE Model May Apply for the Light-Duty Fleet

Technology Name	Abbreviation	Market Data Input File Location	Technology Group
Single Overhead Camshaft Engine with VVT	SOHC	Engines tab	Basic Engines
Double Overhead Camshaft Engine with VVT	DOHC	Engines tab	Basic Engines
Variable Valve Lift	VVL	Engines tab	Basic Engines
Stoichiometric Gasoline Direct Injection	SGDI	Engines tab	Basic Engines
Cylinder Deactivation	DEAC	Engines tab	Basic Engines
Turbocharged Engine	TURBO0	Engines tab	Advanced Engines
Turbocharged Engine with Cooled Exhaust Gas Recirculation	TURBOE	Engines tab	Advanced Engines
Turbocharged Engine with Cylinder Deactivation	TURBOD	Engines tab	Advanced Engines
Advanced Turbocharged Engine, Level 1	TURBO1	Engines tab	Advanced Engines
Advanced Turbocharged Engine, Level 2	TURBO2	Engines tab	Advanced Engines
DOHC Engine with Advanced Cylinder Deactivation	ADEACD	Engines tab	Advanced Engines
SOHC Engine with Advanced Cylinder Deactivation	ADEACS	Engines tab	Advanced Engines
High Compression Ratio Engine	HCR	Engines tab	Advanced Engines
High Compression Ratio Engine with Cooled Exhaust Gas Recirculation	HCRE	Engines tab	Advanced Engines
High Compression Ratio Engine with Cylinder Deactivation	HCRD	Engines tab	Advanced Engines
Variable Compression Ratio Engine	VCR	Engines tab	Advanced Engines
Variable Turbo Geometry Engine[118]	VTG	Engines tab	Advanced Engines
Variable Turbo Geometry Engine with eBooster	VTGE	Engines tab	Advanced Engines
Turbocharged Engine with Advanced Cylinder Deactivation	TURBOAD	Engines tab	Advanced Engines
Advanced Diesel Engine	ADSL	Engines tab	Advanced Engines
Advanced Diesel Engine with Improvements	DSLI	Engines tab	Advanced Engines
Compressed Natural Gas Engine	CNG	Engines tab	Advanced Engines

[118] Technology that enables Miller Cycle ICE.

5-Speed Automatic Transmission	AT5	Transmissions tab	Transmissions
6-Speed Automatic Transmission	AT6	Transmissions tab	Transmissions
7-Speed Automatic Transmission with Level 2 high efficiency gearbox (HEG)	AT7L2	Transmissions tab	Transmissions
8-Speed Automatic Transmission	AT8	Transmissions tab	Transmissions
8-Speed Automatic Transmission with Level 2 HEG	AT8L2	Transmissions tab	Transmissions
8-Speed Automatic Transmission with Level 3 HEG	AT8L3	Transmissions tab	Transmissions
9-Speed Automatic Transmission with Level 2 HEG	AT9L2	Transmissions tab	Transmissions
10-Speed Automatic Transmission with Level 2 HEG	AT10L2	Transmissions tab	Transmissions
10-Speed Automatic Transmission with Level 3 HEG	AT10L3	Transmissions tab	Transmissions
6-Speed Dual Clutch Transmission	DCT6	Transmissions tab	Transmissions
8-Speed Dual Clutch Transmission	DCT8	Transmissions tab	Transmissions
Continuously Variable Transmission[119]	CVT	Transmissions tab	Transmissions
Continuously Variable Transmission with Level 2 HEG[120]`	CVTL2	Transmissions tab	Transmissions
Conventional Powertrain (Non-Electric)	CONV	Vehicles tab	Electrification
12V Micro-Hybrid Start-Stop System	SS12V	Vehicles tab	Electrification
48V Belt Mounted Integrated Starter/Generator	BISG	Vehicles tab	Electrification
Parallel Strong Hybrid/Electric Vehicle with DOHC Engine	P2D	Vehicles tab	Electrification
Parallel Strong Hybrid/Electric Vehicle with DOHC+SGDI Engine	P2SGDID	Vehicles tab	Electrification
Parallel Strong Hybrid/Electric Vehicle with SOHC Engine	P2S	Vehicles tab	Electrification
Parallel Strong Hybrid/Electric Vehicle with SOHC+SGDI Engine	P2SGDIS	Vehicles tab	Electrification
Parallel Strong Hybrid Electric Vehicle with TURBO0 Engine	P2TRB0	Vehicles tab	Electrification
Parallel Strong Hybrid Electric Vehicle with TURBOE Engine	P2TRBE	Vehicles tab	Electrification
Parallel Strong Hybrid Electric Vehicle with TURBO1 Engine	P2TRB1	Vehicles tab	Electrification
Parallel Strong Hybrid Electric Vehicle with TURBO2 Engine	P2TRB2	Vehicles tab	Electrification
Parallel Strong Hybrid Electric Vehicle with HCR Engine	P2HCR	Vehicles tab	Electrification
Parallel Strong Hybrid Electric Vehicle with HCRE Engine	P2HCRE	Vehicles tab	Electrification
Power Split Strong Hybrid/Electric Vehicle with Full Time Atkinson Engine	SHEVPS	Vehicles tab	Electrification
Plug-in Hybrid Vehicle with TURBO1 Engine and 20 miles of electric range	PHEV20T	Vehicles tab	Electrification

[119] Note that the CVT and CVTL2 technologies are not applicable to the Pickup and PickupHT technology classes.
[120] Note that the CVT and CVTL2 technologies are not applicable to the Pickup and PickupHT technology classes.

Plug-in Hybrid Vehicle with TURBO1 Engine and 50 miles of electric range	PHEV50T	Vehicles tab	Electrification
Plug-in Hybrid Vehicle with HCR Engine and 20 miles of electric range	PHEV20H	Vehicles tab	Electrification
Plug-in Hybrid Vehicle with HCR Engine and 50 miles of electric range	PHEV50H	Vehicles tab	Electrification
Plug-in Hybrid Vehicle with Full Time Atkinson Engine and 20 miles of electric range	PHEV20PS	Vehicles tab	Electrification
Plug-in Hybrid Vehicle with Full Time Atkinson Engine and 50 miles of electric range	PHEV50PS	Vehicles tab	Electrification
Battery Electric Vehicle with 200 miles of range	BEV1	Vehicles tab	Electrification
Battery Electric Vehicle with 250 miles of range	BEV2	Vehicles tab	Electrification
Battery Electric Vehicle with 300 miles of range	BEV3	Vehicles tab	Electrification
Battery Electric Vehicle with 350 miles of range	BEV4	Vehicles tab	Electrification
Fuel Cell Vehicle	FCV	Vehicles tab	Electrification
Base Level Tire Rolling Resistance	ROLL0	Vehicles tab	Rolling Resistance
Tire Rolling Resistance, 10% Improvement	ROLL10	Vehicles tab	Rolling Resistance
Tire Rolling Resistance, 20% Improvement	ROLL20	Vehicles tab	Rolling Resistance
Tire Rolling Resistance, 30% Improvement	ROLL30	Vehicles tab	Rolling Resistance
Base Level Aerodynamic Drag Technology	AERO0	Vehicles tab	Aerodynamic Drag
Aerodynamic Drag, 5% Drag Coefficient Reduction	AERO5	Vehicles tab	Aerodynamic Drag
Aerodynamic Drag, 10% Drag Coefficient Reduction	AERO10	Vehicles tab	Aerodynamic Drag
Aerodynamic Drag, 15% Drag Coefficient Reduction	AERO15	Vehicles tab	Aerodynamic Drag
Aerodynamic Drag, 20% Drag Coefficient Reduction	AERO20	Vehicles tab	Aerodynamic Drag
Base Level Mass Reduction Technology	MR0	Platforms tab	Mass Reduction
Mass Reduction – 5.0% of Glider	MR1	Platforms tab	Mass Reduction
Mass Reduction – 7.5% of Glider	MR2	Platforms tab	Mass Reduction
Mass Reduction – 10.0% of Glider	MR3	Platforms tab	Mass Reduction
Mass Reduction – 15.0% of Glider	MR4	Platforms tab	Mass Reduction
Mass Reduction – 20.0% of Glider	MR5	Platforms tab	Mass Reduction

2.2.1.3.2. Medium Duty Vehicles

Although the HDPUV automotive marketplace is not as heterogeneous as its light-duty counterpart, most of the same considerations applicable to the light-duty vehicle fleet (discussed above) apply here as well. Manufacturers regularly update their offerings, albeit at a slightly slower cadence than in the light-duty sector, with investments in research and development resulting in application of new fuel saving technologies and increased capability. The CAFE Model considers many technologies for analysis, with some nearly universally adopted in the analysis fleet, while some others are used occasionally but show future potential. Several emerging technologies included in the analysis, particularly in the hybridization and electrification space, are beginning to appear within this market segment, providing manufacturers the opportunity to attain significant fuel saving gains. As with the light-duty fleet, the CAFE Model effectiveness and cost assumptions attempt to represent a general characterization of fuel saving technologies that may be reasonably applicable for any manufacturer. Some of the technologies that the CAFE Model may apply to HDPUVs use the same technology name and abbreviation as the light-duty technologies; however, the HDPUV technologies are represented by different technology effectiveness values (discussed further below) and when applicable, different technology costs. In addition, this segment includes vehicles whose capability to do "work" is a priority for the vehicle manufacturers and consumers and the standard for HDPUVs reflects this: the work-factor-based standard explicitly accounts for a vehicle's payload and towing capacity.[121] The selected technology options also reflect our engineering judgment about which technologies fulfill the reliability and durability requirements of HDPUVs to perform the aforementioned work.

The fuel saving technologies considered in this analysis for the HDPUV fleet are listed in Table 2-5.

Table 2-5: Fuel Saving Technologies that the CAFE Model May Apply for the HDPUV Fleet

Technology Name	Abbreviation	Market Data Input File Location	Technology Group
Single Overhead Camshaft Engine with VVT	SOHC	Engines tab	Basic Engines
Double Overhead Camshaft Engine with VVT	DOHC	Engines tab	Basic Engines
Stoichiometric Gasoline Direct Injection	SGDI	Engines tab	Basic Engines
Cylinder Deactivation	DEAC	Engines tab	Basic Engines
Turbocharged Engine	TURBO0	Engines tab	Advanced Engines
Advanced Diesel Engine	ADSL	Engines tab	Advanced Engines
Advanced Diesel Engine with Improvements	DSLI	Engines tab	Advanced Engines
5-Speed Automatic Transmission	AT5	Transmissions tab	Transmissions
6-Speed Automatic Transmission	AT6	Transmissions tab	Transmissions
8-Speed Automatic Transmission	AT8	Transmissions tab	Transmissions
8-Speed Automatic Transmission with Level 2 HEG[122]	AT8L2	Transmissions tab	Transmissions
9-Speed Automatic Transmission with Level 2 HEG	AT9L2	Transmissions tab	Transmissions
10-Speed Automatic Transmission with Level 2 HEG	AT10L2	Transmissions tab	Transmissions
Conventional Powertrain (Non-Electric)	CONV	Vehicles tab	Electrification
12V Micro-Hybrid Start-Stop System	SS12V	Vehicles tab	Electrification
Belt Mounted Integrated Starter/Generator	BISG	Vehicles tab	Electrification
Parallel Strong Hybrid/Electric Vehicle with SOHC Engine[123]	P2S (*P2D, P2TRB0*)	Vehicles tab	Electrification

[121] 49 CFR 535.5(a).
[122] This transmisison is only used for HDPUV P2S and PHEV50H technologies.
[123] The P2S, P2D, and P2TRB0 technologies listed in Table 2-2 are all representation of the same "Parallel Strong Hybrid/Electric Vehicle with SOHC Engine" (P2S) technology. The P2S technology was originally simulated by Argonne using the Autonomie model. However, due to limitations of the CAFE Model version used for this analysis (with respect to technology pathway traversal), DOT staff created duplicates of P2S and copied its effectiveness and cost into the P2D and P2TRB0 nodes.

Plug-in Hybrid Vehicle with Basic Engine and 50 miles of electric range[124]	PHEV50H (*PHEV50T*)	Vehicles tab	Electrification
Battery Electric Vehicle with 150 miles of range (for van classes) or 200 miles of range (for pickup classes)	BEV1	Vehicles tab	Electrification
Battery Electric Vehicle with 250 miles of range (for van classes) or 300 miles of range (for pickup classes)	BEV2	Vehicles tab	Electrification
Fuel Cell Vehicle	FCV	Vehicles tab	Electrification
Base Level Tire Rolling Resistance	ROLL0	Vehicles tab	Rolling Resistance
Tire Rolling Resistance, 10% Improvement	ROLL10	Vehicles tab	Rolling Resistance
Tire Rolling Resistance, 20% Improvement	ROLL20	Vehicles tab	Rolling Resistance
Base Level Aerodynamic Drag Technology	AERO0	Vehicles tab	Aerodynamic Drag
Aerodynamic Drag, 10% Drag Coefficient Reduction	AERO10	Vehicles tab	Aerodynamic Drag
Aerodynamic Drag, 20% Drag Coefficient Reduction	AERO20	Vehicles tab	Aerodynamic Drag
Base Level Mass Reduction Technology	MR0	Platforms tab	Mass Reduction
Mass Reduction – 1.4% of Glider	MR1	Platforms tab	Mass Reduction
Mass Reduction – 13.0% of Glider	MR2	Platforms tab	Mass Reduction

2.2.1.4. AC and Off-Cycle Fuel Consumption Improvement Values

The Market Data Input File includes information about AC and OC technologies; however, this information is not currently broken out at a vehicle model level. Instead, historic data and forecast projections are listed for each manufacturer, by regulatory class on the “Credits and Adjustments” tab of the Market Data Input File. The AC and OC data is used for analysis regardless of regulatory scenario. AC and OC fuel consumption improvement values (FCIV), or credits,[125] may significantly impact compliance pathways manufacturers choose. Chapter 3.7 “Simulating OC and AC Efficiency Technologies,” shows model inputs specifying estimated adjustments (all in grams/mile) for improvements to AC efficiency and other OC energy consumption, and for reduced leakage of AC refrigerants with high global warming potential.

For the light-duty fleet, DOT estimated future values based on an expectation that manufacturers already relying heavily on these adjustments would continue do so, and that other manufacturers would, over time, also approach the limits on adjustments allowed for such improvements. Regulatory provisions regarding reporting OC technologies are new, and manufacturers have only recently begun including related detailed information in compliance reporting data. For this analysis, though, such information was not sufficiently complete to support a detailed representation of the application of OC technology to specific vehicle model/configurations in the model year 2022 fleet.

[124] The PHEV50H and PHEV50T technologies listed in Table 2-2 are both representation of the same “Plug-in Hybrid Vehicle with HCR Engine and 50 miles of electric range” (PHEV50H) technology. As with the P2S technology, PHEV50H was originally simulated by Argonne; however, due to the current CAFE Model limitations, DOT staff duplicated PHEV50H into the PHEV50T node.

[125] Adjustments to a vehicle’s fuel economy value based on OC technologies are termed FCIV in NHTSA’s program because they increase the rated fuel economy of a vehicle, whereas the OC benefits are called credits in the EPA program.

At this time, there are no applications for OC and AC in the analysis fleet for HDPUVs. As such, DOT did not consider AC and OC FCIVs in the HDPUV fleet for the current analysis.

2.2.1.5. Engine Configurations

Different engine configurations may affect the cost of the engine and hybridization technologies.[126] In the Market Data Input File, the "engine technology class" column on the vehicles tab identifies the representative engine classification for each vehicle model, allowing the CAFE Model to reference the appropriate powertrain costs in the Technologies Input File that most reasonably align with the observed vehicle (or row). DOT staff assign engine technology classes for all vehicle models present within the analysis fleet, including vehicles that do not otherwise operate using an ICE (e.g., BEVs). If an electric powertrain replaces an ICE, the EM specifications (and hence the associated costs) may be different depending on the capabilities of the engine that is being replaced. The costs in the Technologies Input File (on the engine tab) account for the power output and capability of the gasoline or electric drivetrain.

2.2.1.6. Shared Engines, Transmissions, and Vehicle Platforms

Parts sharing across products is important and common in the industry. Parts sharing helps manufacturers achieve economies of scale, deploy capital efficiently, and make the most of shared research and development expenses, while still presenting a wide array of consumer choices to the market. The CAFE Model takes part sharing into account, with shared engines, transmissions, and MR platforms. Multiple vehicles that share a common part (as recognized in the CAFE Model), will adopt fuel saving technologies affecting that part together. Furthermore, to maintain parts sharing, if a particular technology upgrade cannot be applied to a vehicle, that upgrade also will not be applied to any vehicle sharing the relevant part. In the Market Data Input File vehicle model/configurations that share engines are assigned the same engine code,[127] vehicles that share transmissions have the same transmission code, and vehicles that adopt MR technologies together share the same platform code.

2.2.1.7. Product Design Cycles

Manufacturers often introduce fuel saving technologies at a major redesign of their product or adopt technologies at minor refreshes in between major product redesigns. In most cases, the CAFE Model may apply new fuel saving technologies to a vehicle only in redesign years. If a vehicle shares an engine or transmission, and the shared powertrain part has already incorporated additional fuel savings technology on other vehicle applications, the vehicle may inherit the upgraded shared engine or transmission at refresh or redesign.

To support the CAFE Model accounting for new fuel saving technology introduction as it relates to product lifecycle, the Market Data Input File includes a projection of redesign and refresh years (identified by the "Redesign Years" and "Refresh Years" columns) for each vehicle. DOT staff projected future redesign years and refresh years based on the historical cadence of that vehicle's product lifecycle. For new nameplates, DOT staff considered the manufacturer's treatment of product lifecycles for past products in similar market segments.

2.2.1.7.1. Light-Duty Vehicles

Redesigns are major investments, and require coordination of product development, manufacturing, and marketing and sales. For their light-duty fleet, many manufacturers have redesigned a large portion of products sold in model year 2022 recently, as shown in Table 2-6.

[126] See Chapter 3.1.2 for a detailed discussion of engine classification based on cylinder count and configuration.
[127] Engines (or transmissions) may not be exactly identical, as specifications or vehicle integration features may be different. However, the architectures are similar enough that it is likely the powertrain systems share R&D, tooling, and production resources in a meaningful way.

Table 2-6: Sales Distribution by Age of Vehicle Engineering Design for the Light-Duty Fleet

Most Recent Engineering Redesign Year of the Observed MY 2022 Vehicle	% of MY 2022 Fleet (Unit Sales) by Engineering Design Age	Age of Vehicle Engineering Design	Portion of MY 2022 New Vehicle Sales with Engineering Designs as New or Newer than "Age of Vehicle Engineering Design"
2008	0.4%	14	100.0%
2009	0.7%	13	99.6%
2010	1.2%	12	98.9%
2011	0.9%	11	97.7%
2012	0.1%	10	96.8%
2013	0.1%	9	96.7%
2014	0.8%	8	96.5%
2015	3.3%	7	95.8%
2016	7.6%	6	92.4%
2017	7.4%	5	84.9%
2018	14.2%	4	77.5%
2019	16.7%	3	63.3%
2020	17.0%	2	46.6%
2021	12.9%	1	29.7%
2022	16.7%	0	16.7%

Manufacturers have different business strategies with respect to how frequently products are redesigned. Some manufacturers use shorter product cycles, and others use longer product cycles. Some manufacturers may use a shorter redesign cycle in one segment, and a longer redesign cycle in another. On average across the industry, manufacturers redesign vehicles every 6.6 years, as shown in Table 2-7. Note, however, that many manufacturers do not compete in the marketplace in every vehicle segment and with at least three relatively new entrants we have yet to see redesigns.

Table 2-7: Sales Weighted Average Time between Engineering Redesigns, by Manufacturer and Vehicle Technology Class, for the Light-Duty Fleet

Manufacturer	SmallCar	SmallCarPerf	MedCar	MedCarPerf	SmallSUV	SmallSUVPerf	MedSUV	MedSUVPerf	Pickup	PickupHT	All Classes
BMW	5.6	6.2	6.4	6.7	6.2	6.1	6.2	6.4	-	-	6.3
Ford	-	-	-	9.0	7.1	7.2	8.6	8.1	7.0	6.0	7.2
GM	7.0	6.0	6.4	6.3	5.4	-	6.1	6.4	8.7	6.0	6.2
Honda	6.0	5.7	4.9	5.2	5.0	6.0	6.7	7.0	6.0	-	5.8
Hyundai	5.8	5.8	5.3	5.0	5.1	5.0	8.1	5.4	6.0	-	5.3
Kia	5.1	5.0	5.0	5.1	5.1	5.2	5.0	5.0	-	-	5.1
JLR	-	9.0	8.5	8.5	6.4	6.3	7.5	8.4	-	-	8.0

Karma	-	-	-	8.7	-	-	-	-	-	-	8.7
Lucid	-	-	-	10.0	-	-	-	-	-	-	10.0
Mazda	5.0	6.1	-	-	6.3	7.0	7.0	-	-	-	6.4
Mercedes-Benz	5.2	-	5.5	6.1	6.3	7.0	8.1	7.4	-	-	6.7
Mitsubishi	6.8	-	-	-	6.3	-	-	-	-	-	6.4
Nissan	6.1	-	6.0	6.2	6.8	7.2	6.1	6.2	8.0	7.4	6.6
Rivian		-	-	-	-	-	-	10.0	-	10.0	10.0
Stellantis	7.0	-	7.5	7.8	7.7	7.3	7.6	7.2	11.3	8.3	7.7
Subaru	5.1	7.5	5.0	-	5.0	5.0	5.0	-	-	-	5.1
Tesla	-	-	9.0	9.0	-	-	-	9.0	-	-	9.0
Toyota	6.0	9.2	6.1	6.8	6.9	6.9	7.5	6.2	8.0	9.0	6.9
Volvo	-	-	7.1	7.2	7.0	7.0	7.0	7.0	-	-	7.0
VWA	6.2	6.5	6.3	7.5	6.3	7.3	6.1	7.4	-	-	6.5
Industry Average	5.9	6.4	6.0	7.3	6.0	6.7	7.0	7.2	7.8	6.9	6.6

Even for manufacturers with similar times between redesigns, offering products in similar segments, the expected timing of product redesigns is often out of phase. When considering year-by-year analysis of standards, the timing of redesigns and the timing between redesigns often affect projected compliance pathways. As shown in Table 2-8, many manufacturers have very recently redesigned significant products, and will have some time before they are expected to redesign these products again. The timing of redesigns, and the duration between redesigns affect how quickly manufacturers may respond to standards.

Table 2-8: Sales Weighted Average Age of Engineering Design in MY 2022, by Manufacturer and Vehicle Technology Class, for the Light-Duty Fleet

Manufacturer	SmallCar	SmallCarPerf	MedCar	MedCarPerf	SmallSUV	SmallSUVPerf	MedSUV	MedSUVPerf	Pickup	PickupHT	All Classes
BMW	6.0	3.6	3.0	2.9	4.2	4.0	3.0	2.7	-	-	3.4
Ford	-	-	-	7.0	1.9	1.4	5.2	2.5	1.5	1.0	2.2
GM	5.7	2.0	5.6	3.7	3.3	-	2.1	2.7	6.6	3.0	3.5
Honda	2.2	0.5	3.9	3.2	0.0	3.0	2.3	4.9	5.0	-	2.5
Hyundai	2.8	2.2	2.0	2.4	1.7	3.1	0.4	1.4	0.0	-	1.8
Kia	2.7	2.7	1.0	3.1	3.2	1.2	0.2	1.6	-	-	2.4
JLR	-	8.0	6.0	6.0	2.8	2.3	3.9	4.8	-	-	4.4
Karma	-	-	-	1.0	-	-	-	-	-	-	1.0
Lucid	-	-	-	0.0	-	-	-	-	-	-	0.0
Mazda	3.0	3.8	-	-	4.1	2.0	6.0	-	-	-	4.3
Mercedes-Benz	3.0	-	2.1	1.6	1.9	5.8	2.2	2.4	-	-	3.0

Mitsubishi	8.0	-	-	-	2.7	-	-	-	-	-	3.7
Nissan	2.1	-	3.0	4.1	2.4	4.6	0.0	2.6	0.0	6.0	2.3
Rivian	-	-	-	-	-	-	-	0.0	-	0.0	0.0
Stellantis	6.0	-	11.0	11.9	4.5	1.0	4.1	1.3	13.0	5.3	4.5
Subaru	5.0	0.0	2.0	-	3.0	2.0	3.0	-	-	-	2.9
Tesla	-	-	5.0	3.8	-	-	-	2.5	-	-	3.4
Toyota	2.7	0.7	4.0	4.5	4.6	4.3	1.6	1.9	6.0	0.0	3.6
Volvo	-	-	3.1	1.5	3.0	2.7	4.4	5.5	-	-	4.0
VWA	2.9	1.9	3.3	3.5	2.5	4.9	3.4	3.9	-	-	2.9
Industry Average	2.8	1.7	3.6	5.2	2.9	3.1	3.1	2.5	4.2	2.7	3.1

Table 2-9 shows the resultant portion of each manufacturers MY 2022 total light-duty vehicle production volume (for the U.S. market) expected to be redesigned in each MY through 2035.

Table 2-9: Portion of Production Redesigned in Each MY Through 2035 for the Light-Duty Fleet

Manufacturer	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
BMW	4%	4%	8%	31%	41%	10%	2%	5%	17%	22%	34%	20%	2%	13%
Ford	7%	5%	13%	0%	4%	43%	18%	15%	2%	5%	7%	33%	21%	7%
GM	1%	0%	33%	44%	9%	13%	0%	17%	8%	45%	9%	20%	17%	3%
Honda	46%	39%	0%	9%	3%	24%	41%	12%	11%	4%	45%	5%	23%	12%
Hyundai	33%	4%	27%	8%	24%	31%	7%	29%	8%	12%	45%	2%	31%	10%
JLR	17%	28%	8%	4%	41%	0%	0%	1%	4%	25%	46%	6%	13%	9%
Karma	0%	0%	0%	0%	100 %	0%	0%	0%	0%	0%	0%	0%	0%	0%
Kia	6%	19%	20%	25%	33%	2%	19%	17%	28%	33%	2%	19%	17%	25%
Lucid	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100 %	0%	0%	0%
Mazda	0%	62%	12%	4%	0%	23%	0%	58%	15%	0%	0%	0%	38%	47%
Mercedes-Benz	15%	27%	7%	5%	21%	17%	19%	7%	35%	12%	7%	4%	21%	5%
Mitsubishi	48%	0%	31%	21%	0%	0%	48%	0%	31%	21%	0%	0%	48%	0%
Nissan	22%	7%	13%	16%	18%	2%	33%	5%	26%	13%	21%	0%	10%	29%
Rivian	100 %	0%	0%	0%	0%	0%	0%	0%	0%	0%	100 %	0%	0%	0%
Stellantis	26%	4%	23%	41%	1%	17%	1%	13%	27%	4%	24%	20%	10%	1%
Subaru	4%	26%	38%	31%	0%	0%	26%	42%	31%	0%	1%	26%	38%	31%
Tesla	0%	0%	0%	6%	40%	0%	0%	45%	9%	0%	0%	0%	6%	40%
Toyota	13%	10%	29%	18%	24%	2%	4%	10%	18%	25%	42%	2%	4%	3%
Volvo	0%	30%	2%	29%	30%	0%	0%	10%	30%	2%	29%	30%	0%	0%
VWA	20%	3%	37%	19%	13%	2%	18%	5%	32%	19%	18%	4%	20%	1%
Industry Average	17%	11%	21%	21%	14%	14%	13%	16%	17%	16%	23%	13%	16%	11%

2.2.1.7.2. Medium Duty Vehicles

Unlike for the light-duty fleet, recent compliance data was not readily available for a large portion of the HDPUV fleet that was used in this analysis. The fleet also included new entrants to the market who have only one generation of vehicle. As such, for some vehicle models/configurations evaluated, DOT staff could not reliably determine the most recent engineering design. Thus, when projecting future redesign cycles for those vehicles, DOT staff relied on product lifecycles of past and current products in similar market segments. For electric-vehicle-only manufacturers that are relatively new entrants to the market, we assumed that their vehicles would not be "redesigned" (as defined for our modeling purposes) for several years. This is because these vehicles already use a significant amount of advanced fuel economy-improving technologies, like electrified powertrains and lightweight and aerodynamic body styles.

As can be seen from Table 2-10, about a quarter of the entire HDPUV fleet includes only the DOT projections of future engineering design cycles. However, of the information that was available, and as shown in Table 2-10, approximately half of the HDPUV fleet's age was five years or newer in model year 2022.

Table 2-10: Sales Distribution by Age of Vehicle Engineering Design for the HDPUV Fleet

Most Recent Engineering Redesign Year of the Observed MY 2022 Vehicle	% of MY 2022 Fleet (Unit Sales) by Engineering Design Age	Age of Vehicle Engineering Design	Portion of MY 2022 New Vehicle Sales with Engineering Designs as New or Newer than "Age of Vehicle Engineering Design"
2003	8.8%	19	100.0%
2007	3.1%	15	91.2%
2012	1.7%	10	88.1%
2015	44.7%	7	86.4%
2016	0.1%	6	41.7%
2017	18.2%	5	41.6%
2019	23.4%	3	23.4%
2022	0%	0	0%

On average across the industry, manufacturers redesigned their HDPUV vehicles every 6.2 years, as shown in Table 2-11. However, as shown in Table 2-12, model year 2022 HDPUV fleet for many manufacturers was generally older when compared to their light-duty counterparts. As with the light-duty fleet, the timing and the duration between redesigns affect how quickly manufacturers may respond to standards within the HDPUV segment. In this segment, manufacturers are not as driven by consumer preference to redesign vehicles as compared to light-duty segment. HDPUV consumers value the vehicles for capability and being able to do work consistently and reliably.

Table 2-11: Sales Weighted Average Time between Engineering Redesigns, by Manufacturer and Vehicle Technology Class, for the HDPUV Fleet

Manufacturer	Pickup2b	Van2b	Pickup3	Van3	All Classes
Ford	6.0	5.9	6.0	5.8	5.9
GM	6.0	9.2	6.0	9.2	6.9
Mercedes-Benz	-	6.8	-	6.8	6.8
Nissan	5.5	6.0	-	-	6.0
Stellantis	6.0	5.2	6.0	-	5.8
Industry Average	6.0	6.5	6.0	7.4	6.2

Table 2-12: Sales Weighted Average Age of Engineering Design in MY 2022, by Manufacturer and Vehicle Technology Class, for the HDPUV Fleet

Manufacturer	Pickup2b	Van2b	Pickup3	Van3	All Classes
Ford	5.0	7.0	5.0	7.0	6.0
GM	7.0	19.0	7.0	19.0	10.2
Mercedes-Benz	-	15.0	-	15.0	15.0
Nissan	6.0	10.0	-	-	9.7
Stellantis	3.0	3.0	3.0	-	3.0
Industry Average	5.3	9.3	5.2	13.6	7.0

Table 2-13 shows the resultant portion of each manufacturers model year 2022 total HDPUV vehicle production volume (for the U.S. market) expected to be redesigned in each model year through 2035.

Table 2-13: Portion of Production Redesigned in Each MY Through 2035 for the HDPUV Fleet

Manufacturer	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
Ford	0%	59%	0%	41%	0%	12%	0%	47%	41%	0%	0%	12%	0%	88%
GM	0%	73%	0%	27%	0%	73%	0%	0%	0%	27%	0%	73%	0%	0%
Mercedes-Benz	0%	100%	0%	0%	0%	0%	100%	0%	0%	0%	0%	100%	0%	0%
Nissan	0%	93%	7%	0%	0%	0%	93%	7%	0%	0%	0%	93%	7%	0%
Stellantis	0%	0%	0%	100%	0%	0%	0%	0%	29%	71%	0%	0%	0%	29%
Industry Average	0%	52%	0%	48%	0%	29%	5%	18%	23%	25%	0%	34%	0%	41%

2.2.2. Characterizing Safety, Economic, and Compliance Positions

In addition to characterizing technologies, some information in the Market Data Input File supports economic calculations in the CAFE Model.

2.2.2.1. Safety Classes

The CAFE Model considers the potential safety effect of MR technologies and crash compatibility of different vehicle types. Mass reduction technologies lower the vehicle's curb weight, which may change crash compatibility and safety, depending on the type of vehicle. DOT staff assign each vehicle in the Market Data Input File a "safety class" (identified by the "Safety Class" column on the vehicles tab) that best aligns with the mass-size-safety analysis. The three safety classes are as follows: passenger car, CUV/minivan, and light truck. All HDPUVs are categorized in the light truck safety class.

Initial curb weight data, as recorded in the Market Data Input File, factor into the mass-size-safety analysis. In nearly all cases, DOT staff sourced curb weight data appearing in the Market Data Input File from manufacturer specification sheets. The curb weight data on the specification sheets may be generally representative of the weight of a vehicle row, but some deviation from that reported curb weight is expected depending on the option content of represented vehicles, and manufacturing variations.

2.2.2.2. Labor and Modeled Vehicles

The CAFE Model includes procedures to consider the direct labor impacts of manufacturers' response to CAFE regulations, considering the assembly location of vehicles, engines, and transmissions, the percent

U.S. content (that reflects percent U.S. and Canada content),[128] and the dealership employment associated with new vehicle sales. Labor information, by vehicle, is included in the Market Data Input File. Sales volumes included in and adapted from the market data also influence total estimated direct labor projected in the analysis. See Chapter 6.2.5 for further discussion of the labor utilization analysis.

For the duration of the analysis, the percent U.S. content is held constant for each vehicle row. In practice, this may not be the case. Changes to trade policy, tariff policy, and the EV Federal tax credits (see Chapter 2.5.2.2) may affect percent U.S. content in the future. Also, some technologies may be more or less likely to be produced in the United States, and if that is the case, their adoption could affect future U.S. content.

The labor hours projected in the Market Data Input File per unit transacted at dealerships, per unit produced for final assembly, per unit produced for engine assembly, and per unit produced for transmission assembly are projected to remain constant for the duration of the analysis, and the origin of these activities is projected to remain unchanged. In practice, it is reasonable to expect that plants could move locations, or engine and TRANS are replaced by another fuel saving technology (like EMs and fixed gear boxes) that could require a meaningfully different amount of assembly labor hours.

Table 2-14 shows sales weighted percent U.S. content by manufacturer, by regulatory class, for passenger cars (PC) and light trucks (LT), collected through American Automotive Labeling Act (AALA) reports required by 49 CFR Part 583. Information was not available for most vehicles in the HDPUV because 49 CFR Part 583 only covers vehicles up to 8,500 GVWR. We used the AALA data available for HDPUVs and supplemented it further through data collected directly from manufacturers' websites. The methodology is described in greater detail in Chapter 6.2.5.

Table 2-14: Sales Weighted Percent U.S. Content by Manufacturer, by Light-Duty Regulatory Class[129]

Manufacturer	PC	LT	Total MY 2022 Sales Weighted Percent U.S. Content	Portion of Vehicles Assembled in the U.S.	Portion of Engines Assembled in the U.S.	Portion of Transmissions Assembled in the U.S.
BMW	7.0%	35.8%	20.2%	18.2%	0.0%	0.0%
Mercedes-Benz	0.5%	33.4%	17.0%	21.6%	2.0%	0.0%
Stellantis	54.9%	56.0%	54.4%	37.0%	18.5%	34.6%
Ford	36.8%	42.9%	39.1%	63.6%	63.6%	86.4%
GM	30.4%	39.8%	37.5%	81.1%	61.1%	72.2%
Honda	54.3%	66.8%	54.0%	84%	82.0%	70.0%
Hyundai	12.2%	11.6%	14.9%	17.7%	10.1%	6.3%
Kia	16.6%	29.2%	23.8%	30.8%	17.9%	15.4%
JLR	5.9%	2.8%	0.3%	0.0%	0.0%	14.3%
Mazda	3.7%	1.3%	1.7%	0.0%	0.0%	0.0%

[128] Percent U.S. content was informed by NHTSA. 2023. Part 583 American Automobile Labeling Act Reports. Last Revised: 2023. Available at: https://www.nhtsa.gov/part-583-american-automobile-labeling-act-reports (Accessed: April 10, 2023).
[129] Manufacturers within the fleet but not included in this table (Karma, Lucid) have no percent content data available through the 49 CFR Part 583 American Automotive Labeling Act (AALA) Reports.

Mitsubishi	1.3%	1.6%	9.4%	11.3%	14.5%	12.9%
Nissan	28.5%	36.1%	30.2%	57.9%	33.3%	0.0%
Subaru	36.5%	25.5%	27.3%	50.0%	0.0%	0.0%
Tesla[130]	55.2%	59.9%	61.2%	100.0%	100.0%	100.0%
Toyota	39.1%	32.5%	37.6%	34.0%	38.3%	20.2%
Volvo	9.5%	1.0%	5.4%	18.9%	0.0%	0.0%
VWA	4.7%	12.7%	0.0%	8.3%	0.0%	0.0%

As observed from Table 2-14 manufacturers employ U.S. labor with varying intensity. In many cases, vehicles certifying in the light truck regulatory class have a slightly larger percent U.S. content than vehicles certifying in the passenger car regulatory class.

2.2.2.3. Credit Banks

Manufacturers may over-comply with CAFE standards and bank so-called over compliance credits. As discussed further in preamble Section II.C.2, manufacturers may use these credits later, sell them to other manufacturers, or let them expire. The CAFE Model does not explicitly trade credits between and among manufacturers, but analysts have adjusted starting credit banks to reflect trades that are likely to happen when the simulation begins (in model year 2022). Considering information manufacturers have reported regarding compliance credits, and considering recent manufacturers' compliance positions, DOT staff estimated manufacturers' potential use of compliance credits in earlier model years. The outcome of these efforts attempts to capture manufacturers' choices to deplete their credit banks rather than producing high volume vehicles with fuel saving technologies in earlier model years. Use of these simulated credit banks also avoids unrealistic application of technologies in early analysis years for manufacturers that typically rely on credits. These assumptions are included in the Market Data Input File.

To estimate the size and potential disposition of manufacturer's CAFE compliance credit banks, staff make use of data in NHTSA's CAFE Public Information Center (PIC), which provides public access to a range of information regarding the CAFE program,[131] including manufacturers' credit balances. Compliance data reported in the CAFE PIC is not published in real time, and a gap exists between a given manufacturer's current credit bank status and the data available in the PIC; this lag varies by manufacturer and can be on the order of weeks to years. To address the limitations of the publicly available data, DOT staff examined preliminary compliance data for each manufacturer's fleets in recent model years, as well as verified credit transactions between manufacturers that have been reported to NHTSA. From these sources, staff estimated compliance deficits or surpluses for each fleet based on fuel economy performance, then combined those estimates with credits either acquired from another manufacturer or traded from a model year fleet's surplus.

CAFE credits that are traded between manufacturers are adjusted to preserve the gallons saved that each credit represents.[132,133] The adjustment occurs at the time of application rather than at the time the credits are traded. This means that a manufacturer that has acquired credits through trade, but has not yet applied them, may show a credit balance that is either considerably higher or lower than the real value of the credits when they are applied. For example, a manufacturer that buys 40 million credits from Tesla may show a credit balance in excess of 40 million. However, when those credits are applied, they may be worth only 1/10 as much — making that manufacturer's true credit balance closer to 4 million than 40 million. In this example, such a large discrepancy between the initial and actual credit balances occurs because the adjustment that is

[130] Tesla does not have internal combustion engines, or multi-speed transmissions, even though they are identified as producing engine and transmission systems in the United States in the Market Data Input File.
[131] NHTSA. CAFE: Corporate Average Fuel Economy, Public Information Center. Available at: https://www.nhtsa.gov/corporate-average-fuel-economy/cafe-public-information-center (Accessed: Feb. 21, 2024).
[132] See 49 U.S.C. 32903(f), which requires the credit trading program preserve total oil savings.
[133] CO_2 credits for EPA's program are denominated in metric tons of CO_2 rather than gram/mile compliance credits and require no adjustment when traded between manufacturers or fleets.

applied to Tesla's credits. This adjustment attempts to preserve the total number of consumed gallons by taking into account the CAFE ratings and standards of both manufacturers at the time those credits are applied. Considering that the CAFE rating of an all-electric manufacturer, such as Tesla, ranges between 100 and 700 mpg (depending on the model year being evaluated), when compared to a more typical manufacturer with CAFE ratings in the 30 to 60 mpg range, Tesla's original credits are likely to be devaluated by as much as ten times.

In order to accurately determine each manufacturer's current credit position—inclusive of earned credits (or deficits), acquired credits that have not yet been applied, or transferred credits that have not yet been applied—DOT staff adjusted each credit transaction to reflect the true value of the credit in the current model year and fleet where it resides.[134] Staff reevaluated existing compliance positions for model years 2019-2021 after adjusting credit values and used analyst judgment to resolve deficits in those years. The CAFE program allows manufacturers to pay civil penalties for non-compliance; however, manufacturers cannot comply with the minimum domestic passenger car standard with transferred credits,[135] so a manufacturer must pay civil penalties if it fails to meet that standard. Credits can then be applied to any remaining deficit between the domestic car fleet CAFE and the calculated standard. However, in most other instances, manufacturers have preferred to apply credits when possible. Credits expire five years after they are earned, so in model year 2018 (for example) expiring credits would have been earned in model year 2013. Manufacturers typically find trading partners for expiring credits, and we let no expiring credits go unused if there were opportunities to resolve deficits in model years leading up to model year 2022.

Some manufacturers faced deficits in the model years prior to 2021 that had not yet been resolved, despite holding positive credit balances (of mostly traded credits). These credits were also applied, where appropriate to resolve compliance deficits – including transfers between fleets and credit carry-forward from older model years. In a small number of cases, we assume some small amount of fine payment (aside from the minimum domestic standard) would be required to resolve deficits. All of these actions were required to estimate credit banks in model years 2017-2021 across the industry because all of those credits can be carried forward into the analysis – beginning with model year 2017 credits that expire in model year 2022 and can be used to offset compliance deficits in the first year of the simulation.

Staff reviewed credit balances, estimated the potential that some manufacturers could trade credits based on their projected compliance positions in the No-Action Alternative, and developed inputs that make carried-forward credits available in each of model years 2022-2026, after subtracting credits assumed to be traded to other manufacturers, adding credits assumed to be acquired from other manufacturers through such trades, and adjusting any traded credits (up or down) to reflect their true value for the fleet and model year into which they were traded.[136] When identifying trading partners for credit transactions, staff examined hundreds of individual credit transactions that have occurred over the last decade and attempted to avoid trading credits between manufacturers that have not previously traded. While the specific transactions are considered CBI, manufacturers report to NHTSA the fleet and model year in which the credits were earned, the fleet and model year into which they are traded, and the (unadjusted) quantity of traded credits. DOT staff took a conservative approach, preserving credits in a manufacturer's bank for future use if it was forced to take aggressive compliance actions (defined as applying technologies that did not "pay back" for new car buyers in the first three years of ownership). This ensures that the CAFE Model has the maximal ability to balance the need for technology application against the need to minimize compliance costs in the early years of the program for manufacturers who have accumulated compliance credits.

Manufacturers' estimated credit banks for the domestic car, imported car, and light truck fleets are shown below. While the CAFE Model will transfer expiring credits into another fleet (e.g., moving expiring credits from the domestic car credit bank into the light truck fleet), staff moved some of these credits into the initial banks to improve the efficiency of application and to reflect better both the projected shortfalls of each manufacturer's regulated fleets and to represent observed behavior. For context, a manufacturer that

[134] Because compliance credits are specific to the model year and fleet in which they are earned, even if they are traded between manufacturers, traded credits must be traded *into* a specific model year and fleet.
[135] 49 U.S.C. 32903(g)(4).
[136] The adjustments, which are based upon the CAFE standard and model year of both the party originally earning the credits and the party applying them, were implemented assuming the credits would be applied to the MeY in which they were set to expire. For example, credits traded into a domestic passenger car fleet for model year 2017 were adjusted assuming they would be applied in the domestic passenger car fleet for model year 2022.

produces one million vehicles in a given fleet and experiences a shortfall of 2 mpg would need 20 million credits, adjusted for fuel savings, to offset the shortfall completely.

Table 2-15: Estimated Domestic Car CAFE Credit Banks

	MY 2017	MY 2018	MY 2019	MY 2020	MY 2021
BMW	-	-	-	-	
Mercedes-Benz	-	-	-	-	
Stellantis	2,011,000	4,023,000	5,028,000	5,028,000	8,045,000
Ford	995,000	-	2,484,000	4,968,000	1,031,000
GM	-	1,958,000	3,209,000	2,807,000	3,367,000
Honda	-	-	1,500,000	1,416,000	-
Hyundai	-	-	-	570,000	1,072,000
Kia	-	-	-	-	3,196,000
JLR	-	-	-	-	-
Mazda	-	653,000	-	-	-
Mitsubishi	-	-	-	-	-
Nissan	2,346,000	4,222,000	-	1,129,000	-
Subaru	-	-	-	-	-
Tesla	-	-	-	-	-
Toyota	-	-	16,900,000	5,156,000	9,736,000
Volvo	-	-	-	-	632,000
VWA	281,000	125,000	2,032,000	3,557,000	5,589,000

Table 2-16: Estimated Imported Car CAFE Credit Banks

	MY 2017	MY 2018	MY 2019	MY 2020	MY 2021
BMW	-	990,000	1,320,000	1,452,000	2,639,000
Mercedes-Benz	-	1,020,000	1,564,000	2,380,000	2,720,000
Stellantis	-	-	-	-	-
Ford	6,164,000	-	-	-	-
GM	-	-	4,253,000	3,756,000	-
Honda	-	4,522,000	-	435,000	1,769,000
Hyundai	-	-	-	-	-
Kia	-	1,946,000	3,363,000	4,460,000	3,568,000
JLR	5,383,000	5,580,000	2,036,000	5,120,000	5,248,000
Mazda	1,425,000	-	-	-	-
Mitsubishi	742,000	1,519,000	-	-	-
Nissan	-	-	-	-	-
Subaru	14,329,000	15,235,000	7,228,000	8,431,000	12,231,000
Tesla	-	-	-	-	-
Toyota	1,081,000	1,359,000	1,336,000	2,550,000	1,188,000

Volvo	-	146,000	-	-	-
VWA	-	-	-	-	-

Table 2-17: Estimated Light Truck CAFE Credit Banks

	MY 2017	MY 2018	MY 2019	MY 2020	MY 2021
BMW	-	776,000	1,553,000	1,941,000	2,329,000
Mercedes-Benz	-	-	-	-	-
Stellantis	-	-	230,000	1,484,000	1,257,000
Ford	1,231,000	1,382,000	-	3,720,000	-
GM	-	920,000	2,514,000	942,000	-
Honda	-	-	-	-	-
Hyundai	402,000	-	-	908,000	564,000
Kia	-	-	-	-	-
JLR	-	2,750,000	2,750,000	2,858,000	2,863,000
Mazda	1,116,000	1,840,000	640,000	-	-
Mitsubishi	500,000	136,000	-	-	-
Nissan	1,457,000	1,473,000	-	1,280,000	-
Subaru	3,532,000	3,178,000	4,087,000	91,000	1,860,000
Tesla	-	-	-	-	-
Toyota	8,835,000	5,145,000	11,300,000	7,126,000	5,817,000
Volvo	330,000	2,406,000	993,000	-	2,265,000
VWA	-	-	4,616,000	3,077,000	-

Table 2-18: Estimated HDPUV Credit Banks

	MY 2017	MY 2018	MY 2019	MY 2020	MY 2021
Mercedes-Benz	-	2,820,000	-	-	-
Stellantis	63,160,000	-	-	-	-
Ford	262,000,000	-	-	-	-
GM	193,000,000	-	-	-	-
Nissan	12,713,000	1,173,000	574,000	233,000	-

Manufacturers have not set up HDPUV credit trading accounts with NHTSA, so credit trading in this segment is not currently possible. Therefore, we take reported credits as given and do not conduct any pre-trading steps across manufacturers for HDPUV credits. Staff utilized some within-manufacturer credit trades (i.e., transfers from future model years) to smooth technology application prior to the analysis start year for Ford and GM. Manufacturers are projected to generate excess credits in this space, and these credits can be used during the initial simulation period (e.g., model years 2022 and 2023) for compliance where imposed redesign schedules in these years prevent sufficient technology application to meet standards.

The CAFE Model includes a similar representation of existing credit banks in EPA's CO_2 program. As inputs to this analysis, staff developed the CO_2 compliance credit banks presented below for manufacturers' passenger car (unlike EPCA, the CAA does not require EPA to differentiate between domestic and imported cars) and light truck fleets.

Table 2-19: Estimated Passenger Car CO_2 Credit Banks (metric tons)

	MY 2017	MY 2018	MY 2019	MY 2020	MY 2021
BMW	2,490,000	102,000	186,000	73,000	-
Mercedes-Benz	800,000	500,000	400,000	400,000	70,000
Stellantis	914,000	2,350,000	2,127,000	1,302,000	2,143,000
Ford	-	-	-	499,000	-
GM	929,000	2,060,000	-	1,686,000	877,000
Honda	3,288,000	5,894,000	3,078,000	1,644,000	186,000
Hyundai	-	-	-	-	-
Kia	-	-	31,000	-	33,000
JLR	250,000	-	-	-	-
Mazda	122,000	105,000	-	-	-
Mitsubishi	90,000	97,000	23,000	22,000	-
Nissan	435,000	-	-	-	-
Subaru	861,000	582,000	633,000	555,000	-
Tesla	-	-	-	-	-
Toyota	195,000	579,000	335,000	170,000	52,000
Volvo	42,000	374,000	141,000	95,000	65,000
VWA	-	458,000	256,000	1,000	95,000

Table 2-20: Estimated Light Truck CO_2 Credit Banks (metric tons)

	MY 2017	MY 2018	MY 2019	MY 2020	MY 2021
BMW	1,163,000	37,000	95,000	45,000	73,000
Mercedes-Benz	1,000,000	1,000,000	1,000,000	1,000,000	
Stellantis	3,815,000	9,609,000	8,947,000	7,313,000	9,546,000
Ford	-	-	-	1,380,000	-
GM	1,200,000	3,483,000	-	3,446,000	1,437,000
Honda	1,650,000	3,398,000	2,288,000	1,225,000	1,646,000
Hyundai	-	-	-	-	-
Kia	-	-	15,000	-	-
JLR	750,000	750,000	-	-	-
Mazda	49,000	59,000	-	-	-
Mitsubishi	81,000	106,000	29,000	29,000	-
Nissan	217,000	-	-	-	-
Subaru	605,000	271,000	1,664,000	1,529,000	-
Tesla	-	-	-	-	-
Toyota	917,000	1,028,000	838,000	516,000	-
Volvo	37,000	405,000	176,000	121,000	389,000
VWA	-	553,000	256,000	2,000	104,000

While the CAFE Model does not simulate the ability to trade credits between manufacturers, it does simulate the strategic accumulation and application of compliance credits, as well as the ability to transfer credits between fleets to improve the compliance position of a less efficient fleet by leveraging credits earned by a more efficient fleet. The model prefers to hold on to earned compliance credits within a given fleet, carrying them forward into the future to offset potential future deficits. This assumption is consistent with observed strategic manufacturer behavior dating back to 2009.

From 2009 to present, no manufacturer has transferred CAFE credits into a fleet to offset a deficit in the same year in which they were earned. This has occurred with credits acquired from other manufacturers via trade but not with a manufacturer's own credits. Therefore, the current representation of credit transfers between fleets—where the model prefers to transfer expiring, or soon-to-be-expiring credits rather than newly earned credits—is both appropriate and consistent with observed industry behavior.

This may not be the case for CO_2 standards, though it is difficult to model exactly. The CO_2 program seeded the industry with a large quantity of early compliance credits (earned in model years 2009-2011[137]) prior to the existence formal CO_2 standards. Early credits from model years 2010 and 2011, however, did not expire until 2021. Considering that under the CO_2 program manufacturers simultaneously comply with passenger car and light truck fleets, to more accurately represent the CO_2 credit system the CAFE Model simulates (and, in effect, encourages) intra-year transfers between regulated fleets for the purpose of simulating compliance with the CO_2 standards.

2.2.2.4. Civil Penalty Payment Preferences

EPCA requires that if a manufacturer does not achieve compliance with a CAFE standard in a given model year and cannot apply credits sufficient to cover the compliance shortfall, the manufacturer must pay civil penalties to the federal government. Some manufacturers have sometimes elected to pay civil penalties rather than achieving compliance with CAFE standards.[138] Until recently, such penalties were assessed at $5.50 per 0.1 mpg of residual shortfall (i.e., after applying compliance credits) per vehicle in the noncompliance fleet with the penalty rate being adjusted to $14 for model years 2019 through 2021, to $15 in model year 2022, and to $16 beginning model year 2023 as required under a separate federal statute. Additional adjustments to the rate will be assessed annually as required by law and otherwise as appropriate. If inputs indicate that a manufacturer treats civil penalty payment as an economic choice (i.e., one to be taken if doing so would be economically preferable to applying further technology toward compliance), the CAFE Model, when evaluating the manufacturer's response to CAFE standards in a given model year, will apply fuel-saving technology only up to the point beyond which doing so would be more expensive (after subtracting the value of avoided fuel outlays) than paying civil penalties.

For this analysis, DOT has exercised the CAFE Model with inputs assuming that all light-duty manufacturers will treat civil penalty payment as an economic choice through model year 2026. While DOT expects that only manufacturers with some history of paying civil penalties would actually treat penalty payment as an acceptable option, the CAFE Model does not currently simulate compliance credit trading between manufacturers, and DOT expects that this treatment of penalty payment will serve as a reasonable proxy for compliance credit purchases some manufacturers might actually make through model year 2026 only for the EIS (also known as the "real world") simulations.[139] These input assumptions for model years through 2026 reduce the potential that the model will overestimate technology application in the model years leading up to those for which the agency is finalizing new standards. As in the past CAFE rulemaking analyses (except that supporting the 2020 final rule), DOT has treated manufacturers with some history of fine payment (i.e., BMW, Mercedes-Benz [formerly Daimler], Stellantis [formerly Fiat Chrysler Automobiles (FCA)], Volvo, and

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[137] In response to public comment, EPA eliminated the possible use of credits earned in model year 2009 for future MYs. However, credits earned in model year 2010 and model year 2011 remain available for use.
[138] Fiat Chrysler Automobiles (FCA) paid $77,268,702.50 for its model year 2016 minimum domestic passenger car standard (MDPCS) shortfall, $79,376,643.50 for its model year 2017 MDPCS shortfall, $123,261,187.50 for its model year 2018 MDPCS shortfall and the first of four payments of $112,302,344.00 for its model year 2019 MDPCS shortfall out of a total of $449,209,376.00.Afterwards, Volvo paid an additional civil penalty of $2,282,192.00 for defaulting on a credit carryback plan by failing to earn and carryback sufficient credits from MY2016 to resolve its MY2013 credit shortfall. See NHTSA. 2023. Civil Penalties. Public Information Center. Available at: https://www.nhtsa.gov/corporate-average-fuel-economy/cafe-public-information-center. (Accessed: Feb. 21, 2024).
[139] From MY2012 to model year 2019, numerous manufactuers have conducted CAFE credits trades amongts themselves. See NHTSA. 2023. Credit Status Reports. Public Information Center. Available at: https://one.nhtsa.gov/cafe_pic/home/ldreports/creditStatus (Accessed: December 22, 2023).

Volkswagen (VW)) as continuing to treat civil penalty payment as an acceptable option beyond model year 2026 but has treated all other manufacturers as unwilling to do so beyond model year 2026. Conversely, for the HDPUV fleet, only for purposes of model operation, DOT has treated all manufacturers as unwilling to consider civil penalties as an economic choice during any of the model years covered in this analysis. More information about HDPUV compliance is discussed in the preamble Compliance Section VII.

2.2.2.5. Payback

The CAFE Model uses an “effective cost” metric to evaluate options to apply specific technologies to specific engines, transmissions, platforms, and vehicle model configurations. Expressed on a $/gallon basis, this metric is computed by subtracting the estimated values of avoided fuel outlays, civil penalties, and Federal incentives (i.e., tax credits) from the corresponding technology costs, then dividing the result by the quantity of avoided fuel consumption. The value of fuel outlays is computed over a “payback period” representing the manufacturer’s expectation that consumers will be willing to pay for some portion of fuel savings achieved through higher fuel economy or fuel efficiency. Once the model has applied enough technology to a manufacturer’s fleet to achieve compliance with CAFE and fuel efficiency standards (and CO_2 standards and ZEV programs) in a given model year, the model will apply any further fuel economy or efficiency improvements estimated to produce a negative effective cost (i.e., any technology applications for which avoided fuel outlays during the payback period are larger than the corresponding technology costs). As discussed above in Chapter 1 and below in Chapter 4, DOT staff anticipate that manufacturers are likely to act as if the market is willing to pay for avoided fuel outlays expected during the first 30 months of vehicle operation.

2.2.2.6. Zero Emissions Vehicles

When considering other standards that may affect fuel economy compliance pathways in the reference baseline, NHTSA included projected ZEVs that would be required for manufacturers to meet standards in California and Section 177 states: the Advanced Clean Cars (ACC I) and Advanced Clean Trucks (ACT) programs. NHTSA also included in the reference baseline the main provisions of California’s Advanced Clean Cars II program (ACC II), which has not been granted a Clean Air Act preemption waiver but whose targets manufacturers have indicated that they intend to deploy additional electric vehicles consistent with regardless of whether that waiver is granted.

To support the inclusion of the ZEV programs (ACC I and ACT) and manufacturer commitments consistent with ACC II’s targets in the analysis, DOT staff identified specific vehicle model/configurations that could adopt BEV technology in response to the ZEV program — independent of CAFE standards. These ZEVs are identified in the Market Data Input File as future BEV1, BEV2, BEV3, or BEV4 vehicles. The CAFE Model shifts sales to ZEVs as needed to comply with these programs, assuming sales will be taken from a vehicle with a comparable price and market segment.[140] The Market Data Input File also includes information about the portion of each manufacturer’s sales that occur in California and Section 177 states, which is helpful for determining how many ZEV credits each manufacturer would need to generate in the future to be consistent with the ACC I/ACC II and ACT programs with their own portfolio. These new procedures are described in more detail in Chapter 2.3.

NHTSA also developed an alternative baseline that does not include ACC I, ACT, or manufacturer deployment of electric vehicles that would be consistent with ACC II.

2.3. Technology Effectiveness Values

The next inputs required to simulate manufacturers’ decision-making processes for the year-by-year application of technologies to specific vehicles are estimates of how effective each technology would be at reducing fuel consumption. For this analysis, we use full-vehicle modeling and simulation to estimate the fuel economy improvements that manufacturers could achieve by applying technology to a fleet of vehicles,

[140] While manufacturers may introduce BEVs that are entirely new designs, staff anticipate that simulating BEVs as new versions of existing vehicle model/configurations should represent these designs reasonably for purposes of this analysis, given that CAFE Model inputs should account reasonably for electric powertrains supplanting CONVs.

considering the vehicles' technical specifications and how combinations of technologies interact. Full-vehicle modeling and simulation use physics-based models to predict how combinations of technologies perform as a full system under defined conditions.

A model is a mathematical representation of a system, and simulation is the behavior of that mathematical representation over time. In this analysis, the model is a mathematical representation of an entire vehicle,[141] including its individual components such as the engine and transmission, overall vehicle characteristics such as mass and aerodynamic drag, and the environmental conditions, such as ambient temperature and barometric pressure. We simulate the model's behavior over test cycles, including the 2-cycle laboratory compliance tests (or 2-cycle tests),[142] to determine how the individual components interact. The 2-cycle tests are test cycles used to measure fuel economy for CAFE compliance, and therefore are the relevant test cycles for determining technology effectiveness when establishing CAFE standards. In the laboratory, 2-cycle testing involves sophisticated test and measurement equipment, carefully controlled environmental conditions, and precise procedures to ensure the most repeatable results possible with human drivers. These structured procedures serve as a uniform assessment for fuel economy measurements.

Full-vehicle modeling and simulation was initially developed to avoid the costs of designing and testing prototype parts for every new type of technology. For example, if a truck manufacturer has a concept for a light-weight tailgate and wants to determine the fuel economy impact for the weight reduction, the manufacturer can use physics-based computer modeling to estimate the impact. The vehicle, modeled with the proposed change, can be simulated on a defined test route and under defined test conditions, such as city or highway driving in warm ambient temperature conditions, and compared against the initial vehicle without the change. Full-vehicle modeling and simulation allows the consideration and evaluation of different designs and concepts before building a single prototype. In addition, full vehicle modeling and simulation is beneficial when considering technologies that provide small incremental improvements. These improvements are difficult to measure in laboratory tests due to variations in how vehicles are driven over the test cycle by human drivers, variations in measurement equipment, and variations in environmental conditions.[143]

Full-vehicle modeling and simulation requires detailed data describing individual vehicle technologies and performance-related characteristics. Those data generally come from design specifications, laboratory measurements, and other subsystem simulations or modeling. One example of data used as an input to the full vehicle simulation are engine maps for each engine technology that define how much fuel is consumed by the engine technology across its operating range.

Using full-vehicle modeling and simulation to estimate technology efficiency improvements has two primary advantages over using single or limited point estimates. First, single point estimates generally do not provide accurate effectiveness values because they do not capture complex relationships among technologies. For example, an analysis using single or limited point estimates may assume that one fuel economy-improving technology with an effectiveness value of 5 percent by itself and another technology with an effectiveness value of 10 percent by itself, when applied together achieve an additive improvement of 15 percent. Technology effectiveness often differs significantly depending on the vehicle type (e.g., sedan versus pickup truck) and the way in which the technology interacts with other technologies on the vehicle, as different technologies may provide different incremental levels of fuel economy improvement if implemented alone or in combination with other technologies. Any oversimplification of these complex interactions leads to less accurate and often overestimated effectiveness estimates.

Second, because manufacturers often add several fuel-saving technologies simultaneously when redesigning a vehicle, it is difficult to isolate the effect of individual technologies using laboratory measurement of production vehicles alone. Modeling and simulation offer the opportunity to isolate the effects of individual

[141] Each full vehicle model in this analysis is composed of sub-models, which is why the full vehicle model could also be referred to as a full system model, composed of sub-system models.

[142] EPA's compliance test cycles are used to measure the fuel economy of a vehicle. For readers unfamiliar with this process, it is like running a car on a treadmill following a program—or more specifically, two programs. The "programs" are the "urban cycle," or Federal Test Procedure (abbreviated as "FTP"), and the "highway cycle," or Highway Fuel Economy Test (abbreviated as "HFET"), and they have not changed substantively since 1975. Each cycle is a designated speed trace (of vehicle speed versus time) that all certified vehicles must follow during testing. The FTP is meant roughly to simulate stop and go city driving, and the HFET is meant roughly to simulate steady flowing highway driving at about 50 mph.

[143] Difficulty in controlling for such variability is reflected, for example, in 40 CFR 1065.210, Work input and output sensors, which describes complicated instructions and recommendations to help control for variability in real world (non-simulated) test instrumentation set up.

technologies by using a single or small number of initial vehicle configurations and incrementally adding technologies to those initial configurations. This provides a consistent reference point for the incremental effectiveness estimates for each technology and for combinations of technologies for each vehicle type. Vehicle modeling also reduces the potential for overcounting or undercounting technology effectiveness.

An important feature of this analysis is that the incremental effectiveness of each technology and combinations of technologies should be accurate and relative to a consistent reference vehicle. We use the absolute fuel economy values from the full vehicle simulations only to determine relative effectiveness, but not to assign an absolute fuel economy value to any vehicle model or configuration.

For this analysis, the absolute fuel economy value for each vehicle in the analysis fleet is based on CAFE compliance data.[144] For subsequent technology changes, we apply the incremental effectiveness values of one or more technologies to the initial fuel economy value to determine the absolute fuel economy achieved for applying the technology change. We determine the effectiveness values using full vehicle simulations performed in Autonomie, a physics-based full-vehicle modeling and simulation software developed and maintained by the U.S. Department of Energy's (DOE) ANL.

As an example, if a Ford F-150 2-wheel drive crew cab and short bed in the analysis fleet has a fuel economy value of 30 mpg for CAFE compliance, we consider 30 mpg the reference absolute fuel economy value. A similar full vehicle model node in the Autonomie simulation may begin with an average fuel economy value of 32 mpg, and with the incremental addition of a specific technology X its fuel economy improves to 35 mpg, a 9.3 percent improvement. In this example, the incremental fuel economy improvement (9.3 percent) from technology X is applied to the F-150's 30 mpg absolute value.

We determine the incremental effectiveness of technologies as applied to the thousands of unique vehicle and technology combinations in the analysis fleet. Although, as mentioned above, full-vehicle modeling and simulation reduces the work and time required to assess the impact of moving a vehicle from one technology state to another, it would be impractical—if not impossible—to build a unique vehicle model for every individual vehicle in the analysis fleet. Therefore, as discussed in the following chapters, the Autonomie analysis relies on 14 vehicle technology class models that are representative of large portions of the light-duty and HDPUV analysis fleet vehicles. The vehicle technology classes ensure that we reasonably represent key vehicle characteristics in the full vehicle models. The next subchapters discuss the details of the technology effectiveness analysis input specifications and assumptions.

2.3.1. Full-Vehicle Modeling, Simulation Inputs, and Data Assumptions

This analysis uses Argonne's full vehicle modeling and simulation tool, Autonomie, to build vehicle models with different technology combinations to determine the effectiveness of those technologies over simulated regulatory test cycles. We consider over 50 technologies as inputs to the Autonomie modeling.[145] These inputs consist of engine technologies, transmission technologies, powertrain electrification, light-weighting, aerodynamic improvements, and ROLL improvements. Chapter 3 broadly discusses each of the technology groupings definitions, inputs, and assumptions. We include a deeper discussion of the Autonomie modeled subsystems, and how inputs feed the sub models resulting in outputs, in the CAFE Analysis Autonomie Documentation that accompanies this analysis.

We develop Autonomie model inputs considering real-world and compliance test cycle constraints. Examples include but are not limited to using an engine knock model in engine map development, noise-vibration-harshness (NVH) constraints on DEAC logic in the engine map development, and NVH constraints on the number of engine on/off events (e.g., from start/stop 12V micro hybrid systems).

[144] See Chapter 2.2.1 Characterizing Vehicles and their Technology Content for further discussion of CAFE compliance data.
[145] See the following items in the rulemaking docket NHTSA-2023-0022 by filtering for Supporting & Related Material: CAFE Analysis Autonomie Documentation; CompactNonPerfo_2206.csv; CompactPerfo_2206.csv; MidsizeNonPerfo_2206.csv; MidsizePerfo_2206.csv; MidsizeSUVNonPerfo_2206.csv; MidsizeSUVPerfo_2206.csv; PickupNonPerfo_2206.csv; PickupPerfo_2206.csv; SmallSUVNonPerfo_2206.csv; SmallSUVPerfo_2206.csv; ANL - All Assumptions_Summary_NPRM_2206.xlsx; ANL - Data Dictionary_NPRM_2206.xlsx; ANL - Summary of Main Component Performance Assumptions_NPRM_2206.xlsx; C2P_Processed_220811.csv; C2V_Processed_220811.csv; C3P_Processed_220811.csv; C3V_Processed_220811.csv; ANL - All Assumptions Summary - (2b-3) FY22 NHTSA - 220811.xlsx; ANL - Data Dictionary - (2b-3) FY22 NHTSA - 2200811.xlsx; ANL - Summary of Main Component Performance Assumptions - (2b-3) FY22 NHTSA - 220811.xlsx.

One of the important inputs to the Autonomie model is the set of engine fuel map models. The engine map models define the fuel consumption rate for an engine equipped with specific technologies when operating over a variety of engine load (torque) and engine speed conditions. We developed the engine map models by creating a base, or root, engine map and then modifying that root map, incrementally, to isolate the effects of the added technologies. The light-duty engine maps, developed by IAV using their GT-Power modeling tool and the HDPUV engine maps, developed by SWRI using their GT-Power modeling tool, are based on real-world engine designs. One important feature of the IAV's GT Power modeling tool is the embedded IAV knock model, which was also developed using real-world engine data.[146,147] This ensures that the engine maps appropriately include real-world constraints as the Autonomie built vehicles are simulated on the test cycles.

Although the same engine map models are used for all vehicle technology classes, the effectiveness varies based on the characteristics of each class. For example, a compact car with a turbocharged engine will have a different effectiveness value than a pickup truck with the same engine technology type. The engine map model's development and specifications are discussed further in Chapter 3.

Other key Autonomie inputs and assumptions are default values and recommendations from Argonne's technical teams, based on test data and other technical publications.[148] For some Autonomie model inputs (such as, for example, throttle time response and shifting strategies for different transmission technologies), assumptions are based on the latest test data and current market information.[149] The Autonomie tool did not simulate vehicle attributes that were determined to have minimal impacts on fuel economy, like whether a vehicle had a sunroof or leather seats, as those attributes would have trivial impact in the overall analysis.

Because this analysis models 14 different vehicle types (i.e., vehicle classes) to represent the thousands of vehicles in the analysis fleet, improper assumptions about an advanced technology could lead to errors in estimating effectiveness. Autonomie is a sophisticated full-vehicle modeling tool that requires extensive technology characteristics based on both physical and intangible data, like proprietary software (e.g., control strategies for DEAC). We can therefore be confident that using full-vehicle technology effectiveness estimates for every combination of technologies considered in this analysis results in a well-constructed set of relative vehicle fuel economy improvements for use in the CAFE Model.

2.3.2. Defining Vehicle Classes in Autonomie

Argonne builds full-vehicle models and runs simulations for many combinations of technologies, but it does not simulate literally every single vehicle model/configuration in the analysis fleet. Not only would it be impractical to assemble the requisite detailed information specific to each vehicle/model configuration, much of which would likely only be provided on a confidential basis but doing so would increase the scale of the simulation effort by orders of magnitude. Instead, Argonne simulates 14 different vehicle types, or what we refer to as "technology classes." Technology classes are a mean of specifying common technology input assumptions for vehicles that share similar characteristics. Because each vehicle technology class has unique characteristics, the effectiveness of technologies and combinations of technologies is different for each technology class. Conducting Autonomie simulations uniquely for each technology class provides a specific set of simulations and effectiveness data for each technology class.

Ten of these classes correspond to the five light-duty "technology classes" generally used in CAFE analysis over the past several rulemakings, each with two performance levels and corresponding vehicle technical specifications (e.g., small car, small performance car, pickup truck, performance pickup truck, and so on). The high performance and low performance vehicles classifications allow for better diversity in estimating technology effectiveness across the fleet. The remaining four classes correspond to the two sets of heavy-duty pickups and vans in the Class 2b and Class 3 weight categories.

[146] Engine knock in SI engines occurs when combustion of some of the air/fuel mixture in the cylinder does not result from propagation of the flame front ignited by the spark plug, but one or more pockets of air/fuel mixture explodes outside of the envelope of the normal combustion front.
[147] See IAV material submitted to the rulemaking docket NHTSA-2023-0022 by filtering for Supporting & Related Material:; IAV_20190430_Eng 22-26 Updated_Docket.pdf, IAV_Engine_tech_study_Sept_2016_Docket.pdf, IAV_Study for 4 Cylinder Gas Engines_Docket.pdf.
[148] An example of a default assumption is the DEAC methodology within Autonomie. The controller within Autonomie has been developed, using test data, to consider NVH and cold start operation when to enable cylinder deactivation.
[149] See further details in Chapter 2.2 and in Chapter 3's individual technology pathway subchapters.

Argonne developed a vehicle characteristics database to capture vehicle attributes that are used to build the full vehicle models for each technology class. Representative vehicle attributes and characteristics are identified from publicly available information and automotive benchmarking databases such as A2Mac1,[150] Argonne's Downloadable Dynamometer Database (D^3),[151] EPA compliance and fuel economy data,[152] EPA's guidance on the cold start penalty on 2-cycle tests,[153] the 21st Century Truck Partnership,[154,155,156] and industry partnerships.[157] The resulting vehicle technology class characteristics assumptions database consists of over 100 different attributes like vehicle frontal area, drag coefficient, fuel tank weight, transmission housing weight, transmission clutch weight, hybrid vehicle component weights, weights for components that comprise engines and electric machines, tire rolling resistance, transmission gear ratios and final drive ratios.

Argonne then assigns each of the 14 vehicle types a set of initial attributes based on representative values determined from the compiled vehicle databases. For example, the characteristics of a model year 2022 Honda Civic are considered along with a wide range of other compact cars to identify representative characteristics for the compact car technology class models. These vehicle technology class attributes coupled with other technology attributes are compiled as inputs for the full-vehicle Autonomie simulations. The simulations then determine the fuel economy improvement from applying each combination of technologies to the initial technology set.

For each vehicle technology class and for each vehicle attribute, Argonne estimates the attribute value using statistical distribution analysis of publicly available data and data obtained from the A2Mac1 benchmarking database. Some vehicle attributes are based on test data and vehicle benchmarking, like the cold-start penalty for the Federal Test Procedure (FTP) test cycle and vehicle electrical accessories load. Table 2-21 and Table 2-22 show some key attributes that are assigned to the reference vehicles. The CAFE Analysis Autonomie Documentation includes more detail about vehicle attributes used in this analysis,[158] and values for each vehicle technology class are provided with the Autonomie Input and Assumptions Description Files.[159]

[150] A2Mac1: Automotive Benchmarking. Proprietary data. Available at: https://www.a2mac1.com. (Accessed: Dec. 22, 2023). A2Mac1 is subscription-based benchmarking service that conducts vehicle and component teardown analyses. Annually, A2Mac1 removes individual components from production vehicles such as oil pans, electric machines, engines, transmissions, among the many other components. These components are weighed and documented for key specifications which is then available to their subscribers.
[151] Argonne National Laboratory. 2023. Downloadable Dynamometer Database. Energy Systems Division. Available at: https://www.anl.gov/es/downloadable-dynamometer-database. (Accessed: Mar. 28, 2024).
[152] EPA. 2023. Data on Cars used for Testing Fuel Economy: Compliance and Fuel Economy Data. Available at: https://www.epa.gov/compliance-and-fuel-economy-data/data-cars-used-testing-fuel-economy. (Accessed: Apr. 3, 2024).
[153] EPA. 2023. Data on Cars used for Testing Fuel Economy: Compliance and Fuel Economy Data. Available at : https://www.epa.gov/compliance-and-fuel-economy-data/data-cars-used-testing-fuel-economy. (Accesssed: Jan. 4, 2023).
[154] DOE. 2019. 21st Century Truck Partnership: Research Blueprint. Available at: https://www.energy.gov/sites/default/files/2019/02/f59/21CTPResearchBlueprint2019_FINAL.pdf. (Accessed: Dec. 21, 2023).
[155] DOE. 21st Century Truck Partnership: Vehicle Technologies Office. Available at: https://www.energy.gov/eere/vehicles/21st-century-truck-partnership. (Accessed: Apr. 3, 2024).
[156] National Academies of Sciences, Engineering, and Medicine. 2015. Review of the 21st Century Truck Partnership, Third Report. *The National Academies Press:* Washington, D.C. Available at: https://nap.nationalacademies.org/catalog/21784/review-of-the-21st-century-truck-partnership-third-report. (Accessed: Apr. 3, 2024).
[157] North American Council for Freight Efficiency. Research and Analysis. Available at: https://www.nacfe.org/research/overview/. (Accessed: Apr. 3, 2024).
[158] Chapter "Vehicle and Component Assumptions" of the CAFE Analysis Autonomie Documentation.
[159] See the following items in the rulemaking docket NHTSA-2023-0022 by filtering for Supporting & Related Material: CompactNonPerfo_2206.csv; CompactPerfo_2206.csv; MidsizeNonPerfo_2206.csv; MidsizePerfo_2206.csv; MidsizeSUVNonPerfo_2206.csv; MidsizeSUVPerfo_2206.csv; PickupNonPerfo_2206.csv; PickupPerfo_2206.csv; SmallSUVNonPerfo_2206.csv; SmallSUVPerfo_2206.csv; ANL - All Assumptions_Summary_NPRM_2206.xlsx; ANL - Data Dictionary_NPRM_2206.xlsx ANL - Summary of Main Component Performance Assumptions_NPRM_2206.xlsx; C2P_Processed_220811.csv; C2V_Processed_220811.csv; C3P_Processed_220811.csv; C3V_Processed_220811.csv; ANL - All Assumptions Summary - (2b-3) FY22 NHTSA - 220811.xlsx; ANL - Data Dictionary - (2b-3) FY22 NHTSA - 2200811.xlsx; ANL - Summary of Main Component Performance Assumptions - (2b-3) FY22 NHTSA - 220811.xlsx.

Table 2-21: Reference Autonomie Technology Class Attributes, LD[160]

Vehicle Class	Performance Category	0-60 mph Time (s)	Payload (kg)	Towing (kg)	Drag Coefficient	Tire Rolling Resistance	Frontal Area (m2)	Estimated Curb Weight (kg)	Base Elec Acc Load (w)	Cold Start Penalty (bag1/bag2 %) NA:TC[161]
Compact Car	Low	9	N/A	N/A	0.31	0.009	2.3	1337	250	14.3/1.084:15.8/1.096
Midsize Car	Low	8	N/A	N/A	0.3	0.009	2.35	1431	250	14.3/1.084:15.8/1.096
Small SUV	Low	8	N/A	N/A	0.36	0.009	2.65	1633	275	14.3/1.084:15.8/1.096
Midsize SUV	Low	8	N/A	N/A	0.38	0.009	2.85	1746	300	14.3/1.084:15.8/1.096
Pickup	Low	7	650	3000	0.42	0.009	3.25	1675	300	14.3/1.084:15.8/1.096
Compact Car	High	7	N/A	N/A	0.31	0.009	2.3	1835	325	14.3/1.084:15.8/1.096
Midsize Car	High	6	N/A	N/A	0.3	0.009	2.35	1801	325	14.3/1.084:15.8/1.096
Small SUV	High	7	N/A	N/A	0.36	0.009	2.65	2103	350	14.3/1.084:15.8/1.096
Midsize SUV	High	7	N/A	N/A	0.38	0.009	2.85	2011	350	14.3/1.084:15.8/1.096
Pickup	High	7	900	4500	0.42	0.009	3.25	2481	350	14.3/1.084:15.8/1.096

[160] These are the reference points for the baseline vehicles.
[161] NA = Naturally Aspirated. TC = Turbocharged Aspiration.

Table 2-22: Reference Autonomie Technology Class Attributes, HDPUV[162]

Vehicle Class	Performance Category	0-60 mph Time (s)	Towing (lbs)	Test Weight for sizing (lbs)	Drag Coefficient	Tire Rolling Resistance	Frontal Area (m2)	Base Elec Acc Load (w)	Cold Start Penalty (bag1/bag2 %) NA:TC[163]
2b	Van	16	6,000	10,000	0.50	0.009	5.38	1000	14.3/1.084:15.8/1.096
2b	HD Pickup	13	15,000	10,000	0.50	0.009	3.95	1000	14.3/1.084:15.8/1.096
3	Van	20	6,500	14,000	0.60	0.009	5.60	1000	14.3/1.084:15.8/1.096
3	HD pickup	16	18,000	14,000	0.50	0.009	3.95	1000	14.3/1.084:15.8/1.096

162 These are the reference points for the baseline vehicles.
163 NA = Naturally Aspirated. TC = Turbocharged Aspiration.

One notable vehicle attribute is engine mass. We did not believe it appropriate to assign a single engine mass for each vehicle technology class. To account for the difference in weight for different engine types, Argonne performed a regression analysis of engine peak power versus weight, based on attribute data taken from the A2Mac1 benchmarking database. For example, to account for the weight of different engine sizes, like 4-cylinder versus 8-cylinder or turbocharged versus naturally aspirated engines, Argonne developed a relationship curve between peak power and engine weight based on the A2Mac1 benchmarking data. Argonne uses the developed relationship to estimate mass for all engines. The analysis applies secondary weight reduction associated with changes in engine technology by using this linear relationship between engine power and engine weight.

For example, when a vehicle in the light-duty and HDPUV analysis fleets with an 8-cylinder engine adopts a more fuel-efficient 6-cylinder engine, the total vehicle weight reflects the updated engine weight with two fewer cylinders based on the peak power versus engine weight relationship. The Autonomie simulation data accounts for the impact of engine MR on effectiveness directly in the Autonomie simulation data through the application of the above relationship. Engine MR through downsizing is, therefore, appropriately not included as part of vehicle MR technology that is discussed in Chapter 3.4, because doing so would result in double counting the impacts. We use four separate curves for light-duty: Two for naturally aspirated engines with gas and diesel, and two for turbocharged engines for gas and diesel; this improves the precision of the engine weight estimates. We also use two separate curves for HDPUVs: One for gasoline engines and the other for diesel engines.

In addition, we hold some attributes at constant levels within each technology class to maintain vehicle functionality, performance, and utility, including NVH, safety, and other utilities important for customer satisfaction. For example, in addition to the vehicle performance constraints discussed in Chapter 2.3.5, the analysis does not allow the frontal area of the vehicle to change in order to maintain utility like ground clearance, head-room space, and cargo space. Another example is the cold-start penalty used to account for fuel economy degradation for heater performance and emissions system catalyst light-off.[164] This allows the analysis to capture discrete improvements in technology effectiveness while maintaining vehicle attributes that are important like vehicle utility, consumer acceptance, and compliance with criteria emission standards. These constraints are considered as manufacturers consider them in the real world.

2.3.3. Building Representative Vehicles and Vehicle Optimization

Before any simulation is initiated in Autonomie, Argonne must "build" a vehicle by assigning reference technologies and initial attributes to the components of the vehicle model representing each technology class.[165] The reference technologies are technologies that represent the first step on each technology pathway used in the analysis. For example, a compact car is built by assigning it a dual overhead cam engine (DOHC), variable valve timing (VVT), port fuel injection (PFI), a 5-speed automatic transmission AT5), a base level of aerodynamic improvement (AERO0), a base level of rolling resistance improvement (ROLL0), a base level of MR technology (MR0), and corresponding attributes from the Argonne vehicle assumptions database like individual component weights.[166] A reference vehicle will have a unique starting point for the simulation and a unique set of assigned inputs and attributes based on its technology class.

The next step in the process is to run a powertrain sizing algorithm for both the light-duty and HDPUV classes that ensures the built vehicle meets or exceeds defined performance metrics including low-speed acceleration (time required to accelerate from 0-60 mph), high-speed passing acceleration (time required to accelerate from 50-80 mph), gradeability (the ability of the vehicle to maintain constant 65 mph speed on a six percent upgrade), and towing capacity. Together, these performance criteria are widely used by the automotive industry as metrics to quantify vehicle performance attributes that consumers observe and that are important for vehicle utility and customer satisfaction.

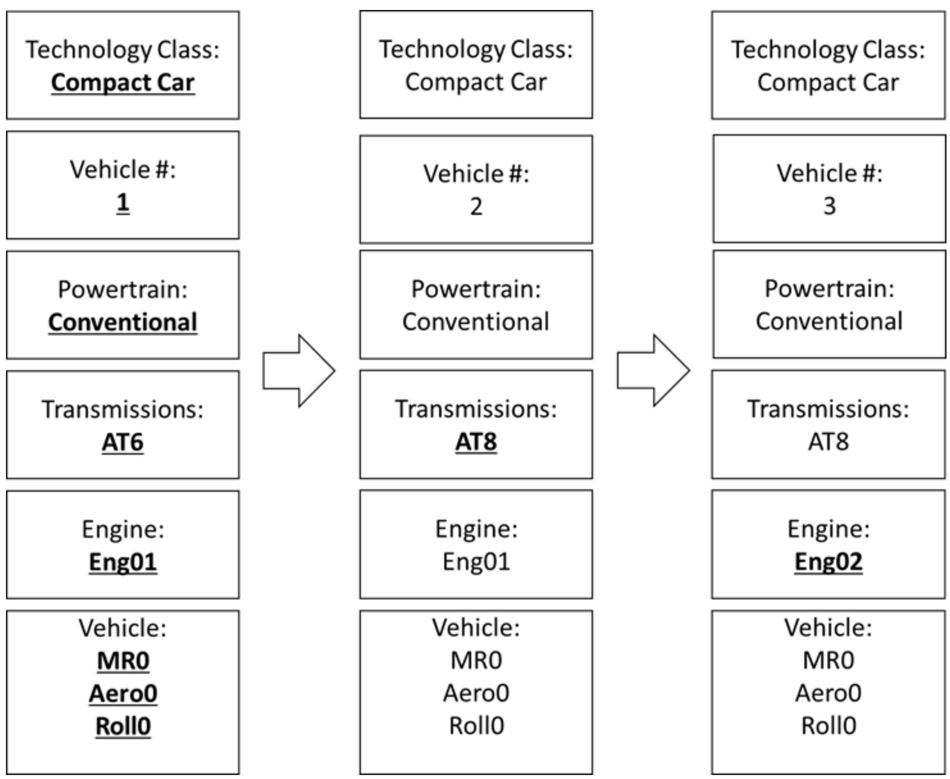
In the compact car example used above, we assign an initial specific engine design and engine power, transmission, aerodynamic drag technology (AERO), ROLL, and MR technologies, and other attributes like

[164] The catalyst light-off is the temperature necessary to initiate the catalytic reaction and this energy is generated from the engine's heat.
[165] Further discussion of this process is in Chapter "Vehicle and Component Assumptions" of the CAFE Analysis Autonomie Documentation.
[166] Further discussion of this setup is in Subchapter "Vehicle and Component Assumptions—Vehicle Component Weight Selection" of the CAFE Analysis Autonomie Documentation.

vehicle weight. If the built vehicle does not meet all the performance criteria as the vehicle is simulated over the defined test cycles in the first iteration, then the engine power is increased to meet the performance requirement. The increase in power is achieved by increasing engine displacement, which might involve an increase in the number of cylinders, which may lead to an increase in the engine weight. This iterative process then determines if the compact car with increased engine power and corresponding updated engine weight meets the required performance metrics. The iterative process stops once all the performance requirements are met for the vehicle, and it is at this point that the compact car technology class vehicle model is ready for simulation.

Autonomie then adopts a single fuel saving technology to the vehicle model, keeping everything else the same except for that one technology and the attributes associated with it. For example, the model applies an 8-speed automatic transmission (AT8) in place of the 6-speed automatic transmission (AT6), which would lead either to an increase or decrease in the total weight of the vehicle based on the technology class assumptions. Autonomie then confirms whether performance metrics are met for this new vehicle model through the previously discussed sizing algorithm and iterations. Once a technology is assigned to the vehicle model and the resulting vehicle meets its performance metrics, the vehicle model is used as an input to the full vehicle simulation. As an example, for just the 6-speed to 8-speed automatic transmission technology update, the initial 14 vehicle models (one for each technology class) are created, plus the 14 new vehicle models with the updated 8-speed automatic transmission, for a total of 28 different vehicle models for simulation. This permutation process is repeated for each of the over 50 technologies considered, which results in hundreds of thousands of optimized vehicle models. Figure 2-2 shows a flow chart of the process for building vehicle models in Autonomie for simulation.

Figure 2-2: Autonomie Technology Adoption Process for Vehicle Building with Compact Car Technology Class as an Example



Some technologies require extra steps for optimization before the vehicle models are built for simulation. For example, the sizing and optimization process is more complex for the electrified vehicles (e.g., HEVs, PHEVs) compared to vehicles with only ICE, as discussed further below in Chapter 2.3.4. During the vehicle building process, the following items are considered for optimization:

- Vehicle weight is adjusted in response to switching from one type of engine or transmission technology to another.
- Vehicle performance is decreased or increased in response to the addition of MR technologies.
- Vehicle performance is decreased or increased in response to the addition of a new technology like AERO or ROLL for the same hybrid electric machine.
- Electrified vehicle battery size is decreased or increased in response to the addition of MR, AERO, and/or ROLL technologies.

Every time a vehicle adopts a new technology, the vehicle weight is updated to reflect the new component weight. For some technologies, the direct weight change is easy to assess. For example, when a vehicle is updated to a higher geared transmission, the weight of the original transmission is replaced with the corresponding transmission weight (e.g., the weight of a vehicle moving from a 6-speed automatic (AT6) to an 8-speed automatic (AT8) transmission is updated based on the 8-speed transmission weight).

For other technologies, like engine technologies, assessing the updated vehicle weight is more complex. As discussed earlier, modeling a change in engine technology involves both the new technology adoption and a change in power since the reduction in vehicle weight leads to lower engine loads, resulting in a resized engine. When a vehicle adopts new engine technology, the associated weight change to the vehicle is accounted for based on the earlier discussed regression analysis of weight versus power. The engine weight regression analysis includes mass data for many different engine technologies that consist of unique components to achieve fuel economy improvements. This regression analysis is technology-agnostic by taking the approach of using engine peak power versus engine weight because it removes biases to any specific engine technology in the analysis. Although using the regression does not estimate the specific weight for each individual engine technology, such as VVT or stoichiometric gasoline direct injection (SGDI), this process provides a reasonable estimate of the weight differences among engine technologies.

Figure 2-3 shows an example of the engine mass regression for the naturally aspirated, forced air induction engines, and Figure 2-4 shows an example of the engine mass regression for diesel engines. Argonne updated the regression for this analysis to reflect the latest data from A2Mac1, which resulted in two changes. First, small naturally aspirated 4-cylinder engines that adopt turbocharging technology reflect the increased weight of associated components like ducting, clamps, the turbocharger itself, a charged air cooler, wiring, fasteners, and a modified exhaust manifold. Second, larger cylinder count engines like naturally aspirated 8-cylinder and 6-cylinder engines that adopt turbocharging and downsized technologies have less weight due to having fewer engine cylinders. For example, a naturally aspirated 8-cylinder engine that adopts turbocharging technology when downsized to a 6-cylinder turbocharged engine appropriately reflects the added weight of turbocharging components, and the lower weight of fewer cylinders. New to this analysis, the same mass regression is done for HDPUVs as shown Figure 2-5.

Figure 2-3: Gasoline Engine Mass Determination as a Function of Power and Type of Air Induction and Engine Type

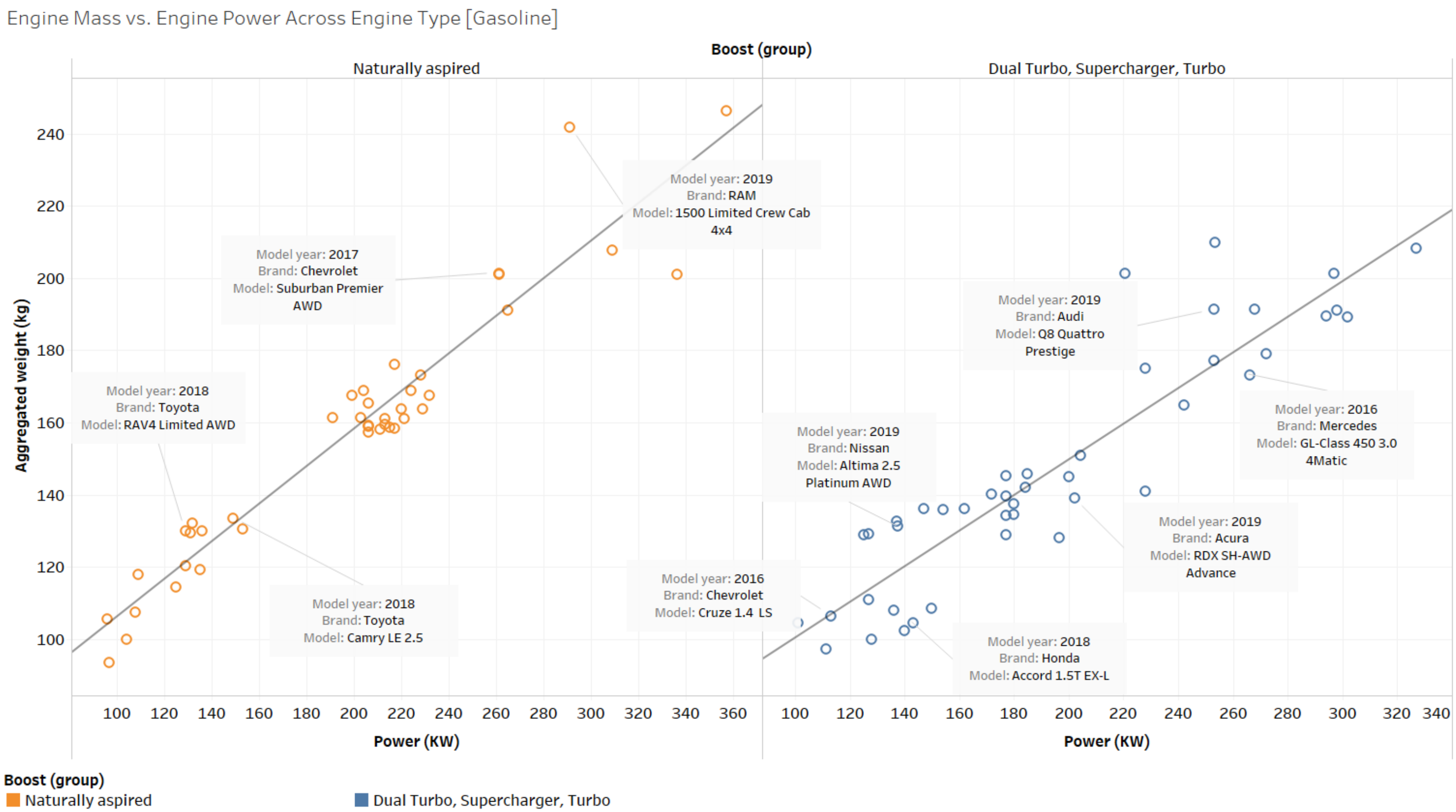


Figure 2-4: Diesel Engine Mass Determination as a Function of Power and Type of Air Induction and Engine Type

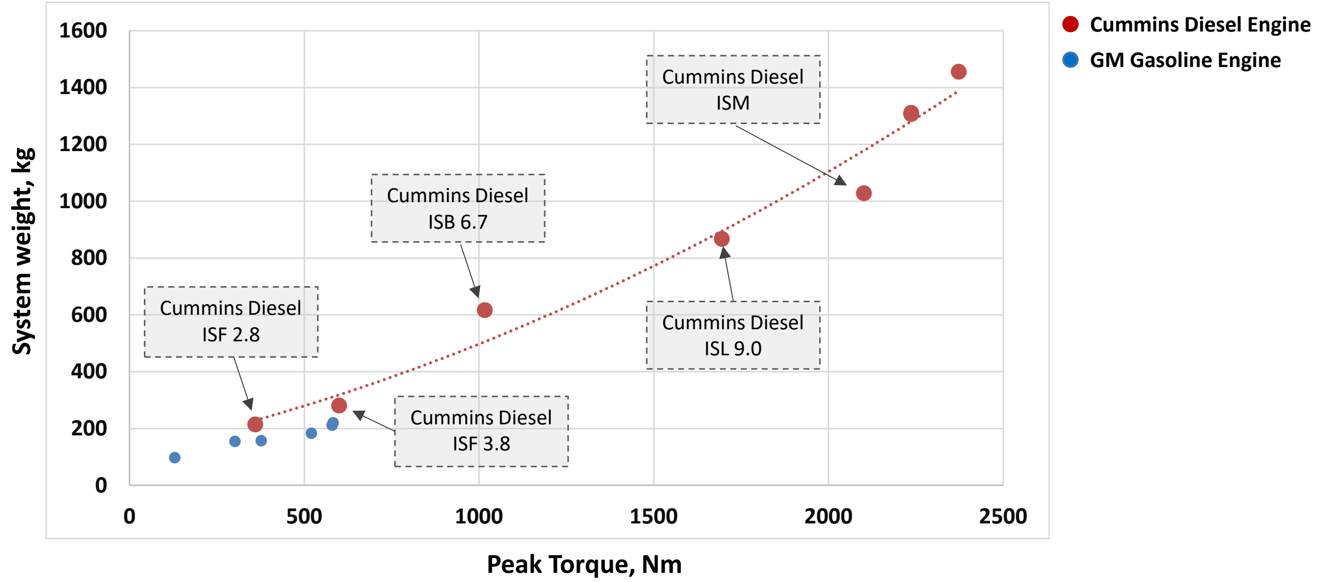
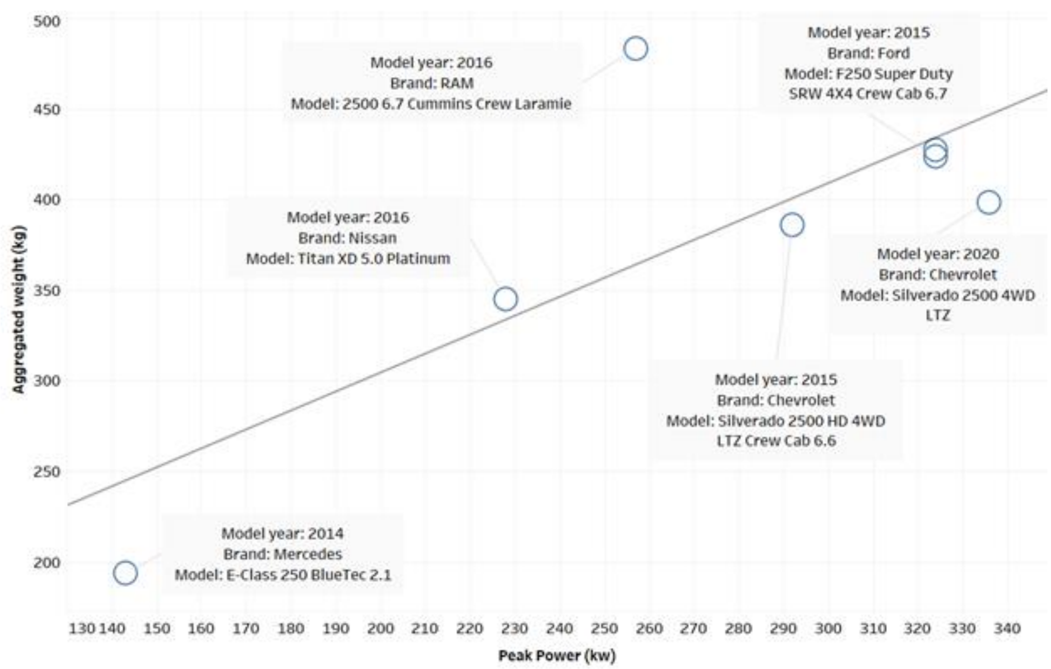


Figure 2-5: HDPUV Engine Mass Determination as a Function of Power and Type of Air Induction and Engine Type

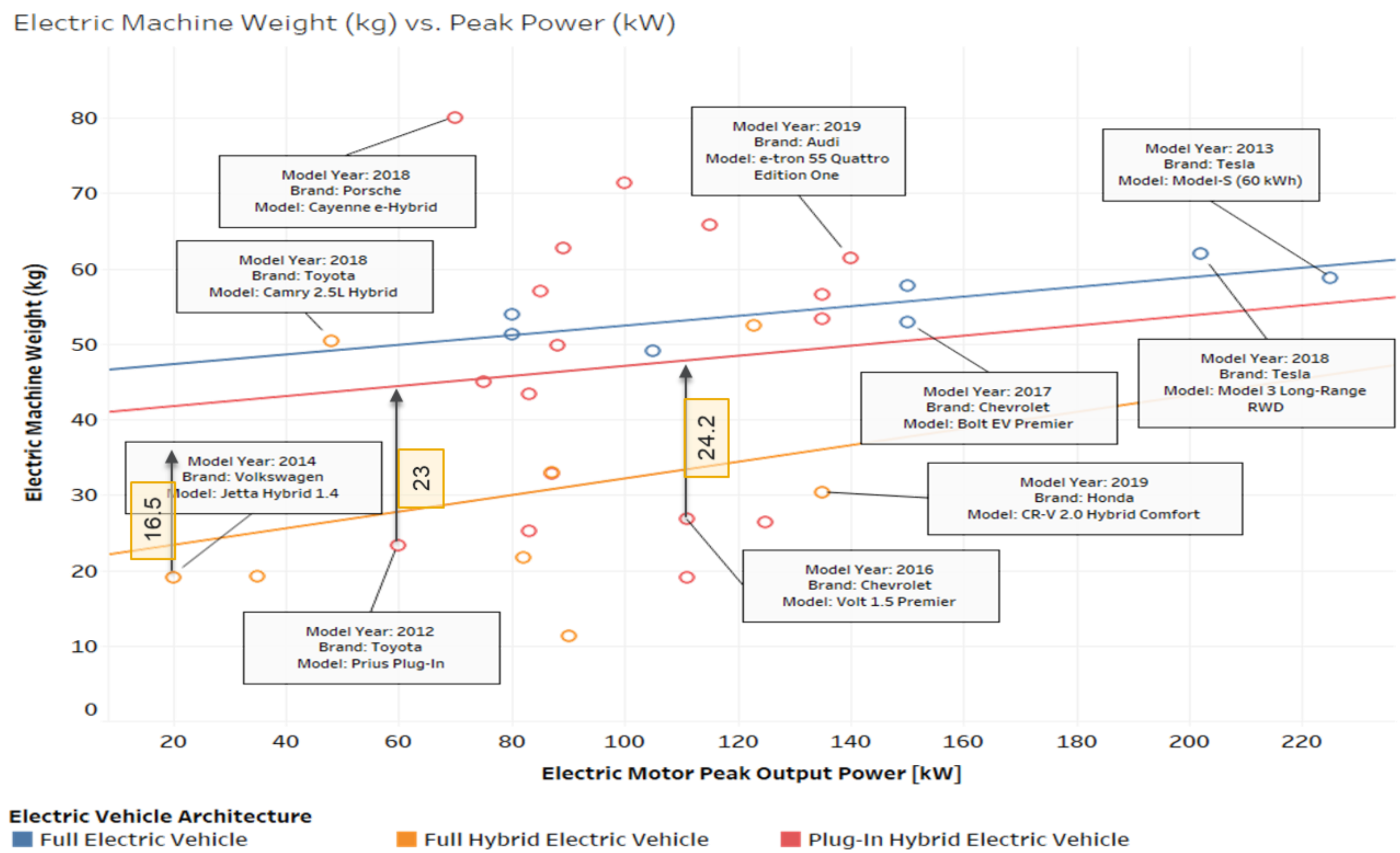


Like conventional vehicle models, Autonomie also builds electrified vehicle models from the ground up. To capture improvements for electrified vehicles for this analysis, Argonne applies the same mass regression analysis process that considers EM weight versus EM power for vehicle models that adopt EMs. Argonne analyzed benchmarking data for hybrid and EVs from the A2Mac1 database to develop a regression curve of

EM peak power versus EM weight.[167] Figure 2-6 below shows the EM mass regression as a function of peak power.

[167] CAFE Analysis Autonomie Documentation Chapter titled “Vehicle and Component Assumptions—Vehicle Component Weight Selection—Light-Duty Vehicles—Electric Drive System Weight Determination.”

Figure 2-6: Electric Motor Mass Determination as Function of Peak Power



2.3.4. Sizing Powertrains

We maintain performance neutrality in the full vehicle simulations by resizing engines, electric machines, and HEV battery packs at specific incremental technology steps. To address product complexity and economies of scale, engine resizing is limited to specific incremental technology changes that would typically be associated with a major vehicle or engine redesign. This is intended to reflect manufacturers' comments to DOT on how they consider engine resizing and product complexity, and DOT's automotive engineers experience with and observations about industry product complexity.

When a powertrain does need to be resized, Autonomie attempts to mimic manufacturers' practices to the greatest extent possible. As discussed earlier, the Autonomie vehicle building process is initiated by building a vehicle model with a base engine, transmission, and other base vehicle technologies. This base vehicle model (for each technology class) is sized to meet a specific set of performance criteria, including acceleration and gradeability.

The modeling also accounts for the industry practice of platform, engine, and transmission sharing to manage component complexity and the associated costs.[168] At a vehicle refresh cycle, a vehicle may inherit an already resized powertrain from another vehicle within the same engine-sharing platform that adopted the powertrain in an earlier model year. In the Autonomie modeling, when a new vehicle adopts fuel saving technologies that are inherited, the engine is not resized (the properties from the reference vehicle are used directly and unchanged) and there may be a small change in vehicle performance. For example, in Figure 2-2 above, Vehicle 2 inherits Eng01 from Vehicle 1 while updating the transmission. Inheritance of the engine with the new transmission may change performance. This example illustrates how manufacturers generally manage manufacturing complexity for engines, transmissions, and electrification technologies.

Autonomie implements different powertrain sizing algorithms depending on the type of powertrain being considered because different types of powertrains contain different components that must be optimized.[169] For example, Autonomie's conventional powertrain (CONV) resizing algorithm considers only the reference power of the conventional engine (e.g., Eng01, a basic VVT engine, is rated at 108 kilowatts and this is the starting reference power for all technology classes), versus the SHEVPS resizing algorithm that must separately optimize engine power, battery size (energy and power), and electric machine power. An engine's reference power rating can either increase or decrease depending on the architecture, vehicle technology class, and whether it includes other advanced technologies.

Performance requirements also differ depending on the type of powertrain because vehicles with different powertrain types may need to meet different criteria. For example, a PHEV powertrain that can travel a certain number of miles on its battery energy alone (i.e., AER, or as performing in electric-only mode) is also sized to ensure that it can meet the performance requirements of a US06 drive cycle in electric-only mode.

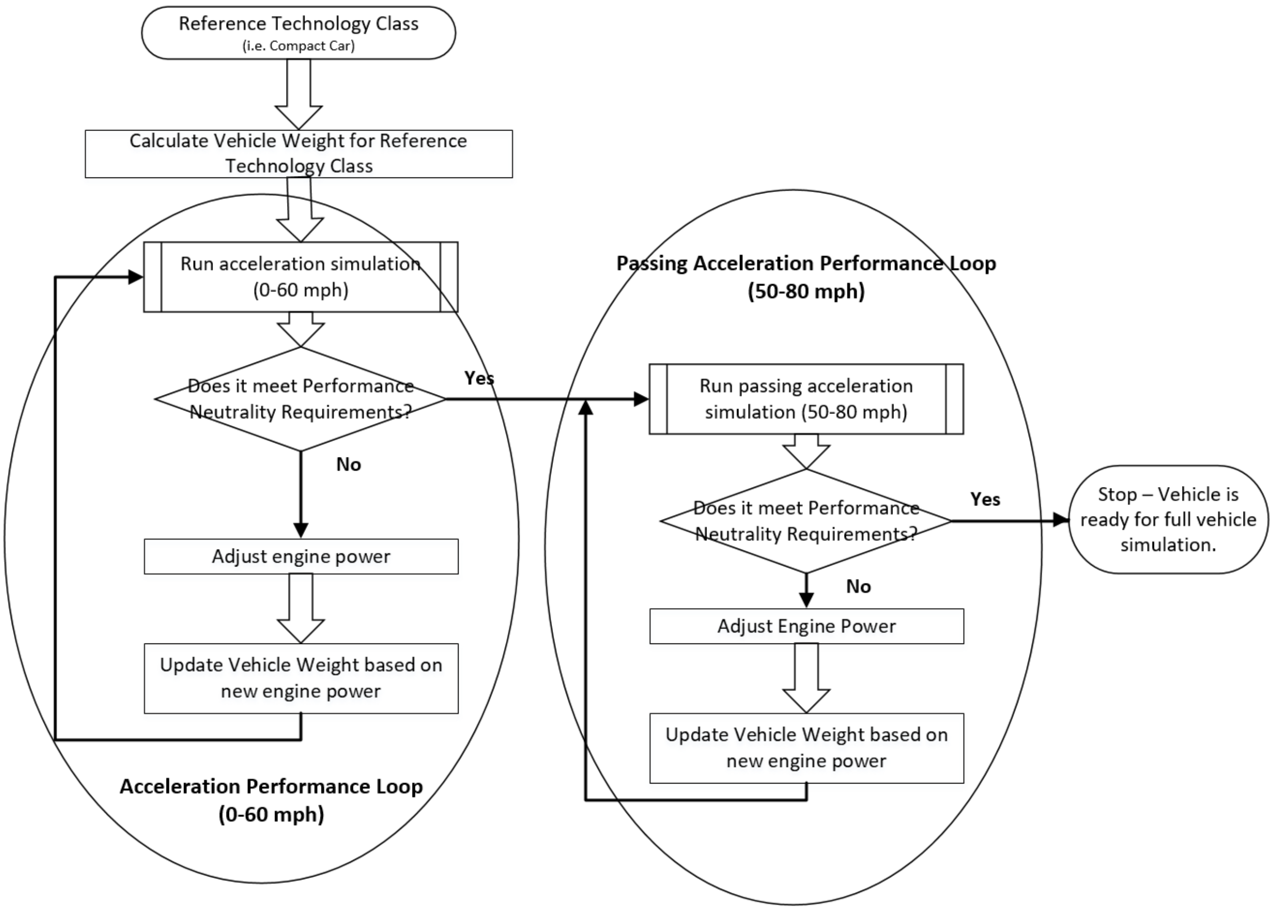
The powertrain sizing algorithm is an iterative process that attempts to optimize individual powertrain components at each step. For example, the sizing algorithm for CONV estimates required power to meet gradeability and acceleration performance and compares it to the reference engine power for the technology class. If the power required to meet gradeability and acceleration performance exceeds the reference engine power, the engine power is updated to the new value. Similarly, if the reference engine power exceeds the gradeability and acceleration performance power, it is decreased to the lower power rating. If the change in power requires a change in the engine design, like increasing displacement (e.g., going from a 1.8-liter to 2.4-liter engine) or increasing cylinder count (e.g., going from an I4 to a V6), the engine weight will also change. The new engine power is used to update the weight of the engine.

Next, the CONV sizing algorithm enters an acceleration algorithm loop to verify low-speed acceleration performance (the time it takes to go from 0 mph to 60 mph). In this step, Autonomie adjusts engine power to maintain a performance attribute for the given technology class and updates engine weight accordingly. Once this performance criterion is met, Autonomie ends the low-speed acceleration performance algorithm loop and enters a high-speed acceleration (the time it takes to go from 50 mph to 80 mph) algorithm loop. Again,

[168] For example, Ford EcoBoost Engines are shared across ten different models in model year 2019. See https://www.ford.com/powertrains/ecoboost/.
[169] Chapter "Vehicle Sizing Process" of the CAFE Analysis Autonomie Documentation.

Autonomie might need to adjust engine power to maintain a performance attribute for the given technology, and it exits this loop once the performance criteria are met. At this point, the sizing algorithm is complete for the CONV based on the designation for engine type, transmission type, aerodynamic improvement type, MR technology, and low rolling resistance technology. Figure 2-7 below shows the sizing algorithm for CONVs. Each circle in the flow chart is a closed loop system and the loop must be completed to move to the next loop; e.g., the acceleration performance loop must be complete before the model sizes components to meet the passing acceleration performance loop. This allows us to avoid under- or oversizing components, engines, and EMs to minimize over and under compliance in the analysis.

Figure 2-7: Conventional Powertrain Closed Loop Sizing Algorithm



Depending on the type of powertrain considered, the sizing algorithms may size to meet the different performance criteria in a different order. For example, the electrified powertrain sizing algorithm considers different requirements, including range and battery power in addition to performance. The powertrain sizing algorithms for electrified vehicles are considerably more complex and are discussed in further detail in Chapter 3.3.4 and the CAFE Analysis Autonomie Documentation.[170]

2.3.4.1. Shift Logic

Transmission shifting logic has a significant impact on vehicle energy consumption. Argonne models shift logic in Autonomie to maximize powertrain efficiency while maintaining acceptable drive quality. The logic used in the Autonomie full vehicle modeling relies on two components: (1) the shifting controller, which provides the logic to select appropriate gears during simulation; and (2) the shifting initializer, an algorithm

[170] CAFE Analysis Autonomie Documentation, Chapter titled "Vehicle Sizing Process—Vehicle Powertrain Sizing Algorithms".

that defines shifting maps (i.e., values of the parameters of the shifting controller) specific to the selected set of modeled vehicle characteristics and modeled powertrain components.[171]

2.3.4.1.1. Shifting Controller

The shift controller is the logic that governs shifting behavior during simulated operation. Inputs from the model inform the shift controller performance. The inputs include the specific engine and transmission and instantaneous conditions in the simulation. The model adjusts shifting logic based on engine characteristics to maximize the advantages of the engine technology. Instantaneous conditions include values such as vehicle speed, driver demand, and a shifting map unique to the full vehicle configuration.[172]

2.3.4.1.2. Shifting Initializer

The shifting initializer is an algorithm that defines shifting maps (i.e., values of the parameters of the shifting controller) specific to the selected set of modeled vehicle characteristics and modeled powertrain components. The shifting initializer is run for every unique combination of vehicle technologies modeled in the Autonomie tool and is an input to the full vehicle simulation. The shifting initializer creates a shifting map that optimizes fuel economy performance for the powertrain and road load combination within the constraints of performance neutrality.[173]

2.3.5. Simulating the Built Vehicles on Test Cycles

After Autonomie builds vehicle models for every combination of technologies and vehicle classes represented in the analysis, Autonomie simulates the vehicles' performance on test cycles to calculate the effectiveness improvement of adding fuel economy-improving technologies to the vehicle. Simulating vehicles' performance using tests and procedures specified by federal law and regulations minimizes the potential variation in determining technology effectiveness.

Autonomie simulates vehicles using a very similar process as the test procedures and energy consumption calculations that manufacturers must use for CAFE and fuel efficiency compliance.[174,175,176] Argonne simulates each vehicle model across several test cycles to evaluate technology effectiveness. For this analysis, both the light-duty and HDPUVs are simulated on the same test cycles.[177] For vehicles with CONVs and micro hybrids, Autonomie simulates the vehicles per EPA 2-cycle test procedures and guidelines.[178] For mild and full HEVs and FCVs, Autonomie simulates the vehicles using the same EPA 2-cycle test procedure and guidelines, and the drive cycles repeat until the initial and final state of charge (SOC) are within a SAE J1711 tolerance. For PHEVs, Autonomie simulates vehicles per similar procedures and guidelines as prescribed in SAE J1711.[179] For BEVs Autonomie simulates vehicles per similar procedures and guidelines as prescribed in SAE J1634.[180]

2.3.6. Implementation in the CAFE Model

While the Autonomie model produces a large amount of information about each simulation run—for a single technology combination, in a single technology class—the CAFE Model only uses two elements of that information: battery costs, and fuel consumption on the city and highway cycles. We combine the fuel economy information from the two cycles to produce a composite fuel economy value for each vehicle, and on

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[171] Chapter "Transmission Shifting" of the CAFE Analysis Autonomie Documentation.
[172] See Chapter "Transmission Shifting" of the CAFE Analysis Autonomie Documentation for more information on the shifting controller.
[173] See Chapter "Transmission Shifting" of the CAFE Analysis Autonomie Documentation for more information on the shifting initializer algorithm.
[174] EPA. 2023. How Vehicles are Tested. Available at: https://www.fueleconomy.gov/feg/how_tested.shtml. (Accessed: Dec. 21, 2023).
[175] Chapter "Test Procedures and Energy Consumption Calculations" of the CAFE Analysis Autonomie Documentation.
[176] EPA. 2017. Test Procedures for Electric Vehicles and Plug-in Hybrids. Draft Summary. Available at: https://www.fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf. (Accessed: Jan. 18, 2024).
[177] See EPA. 2016. Regulatory Impact Analysis. Greenhouse Gas Emissions and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles – Phase 2. EPA-420-R-16-900. Available at: https://nepis.epa.gov/Exe/ZyPDF.cgi/P100P7NS.PDF?Dockey=P100P7NS.PDF. (Accessed: May 31, 2023).
[178] 40 CFR 600.116-12 Special procedures related to EVs and HEVs.
[179] PHEV testing is broken into several phases based on SAE J1711: charge-sustaining on the city cycle, charge-sustaining on the HWFET cycle, charge-depleting on the city and HWFET cycles.
[180] SAE International. 2017. Battery Electric Vehicle Energy Consumption and Range Test Procedure. SAE International. J1634.Available at: https://saemobilus.sae.org/content/j1634_201707. (Accessed: Apr. 3, 2024).

each fuel for dual-fueled light-duty vehicles. Plug-in hybrids are the only dual-fuel vehicles in the Autonomie simulation, and they require efficiency estimates for operation on both gasoline and electricity, as well as an estimate of the utility factor, or the number of miles driven on each fuel. The fuel economy information for each technology combination within each technology class is converted into a single number for use in the CAFE Model. For HDPUVs, we produce a fuel consumption value.[181]

Each Autonomie simulation record represents a unique combination of technologies, and we create a technology "key" (also referred to as a technology state vector) that describes all the technology content associated with a record. The 2-cycle fuel economy of each combination is converted into fuel consumption (gallons per mile) and then normalized relative to the starting point for the simulations. In each technology class, the combination with the lowest technology content is the VVT (only) engine, with a 5-speed transmission, no electrification, and no body-level improvements (MR, aerodynamic improvements, or low rolling resistance tires). This is the reference point (for each technology class) for all of the effectiveness estimates in the CAFE Model. The improvement factors that the model uses are a given combination's fuel consumption improvement relative to the reference vehicle in its technology class.

The fuel economy improvements for technologies in the CAFE Model are derived from the database of Autonomie's detailed full-vehicle modeling and simulation results. To incorporate the results of the combined Autonomie databases, while still preserving the basic structure of the CAFE Model's technology subsystem, it is necessary to translate the points in this database into corresponding locations defined by the technology pathways. By recognizing that most of the pathways are unrelated and are only logically linked to designate the direction in which technologies are allowed to progress, it is possible to condense the paths into a smaller number of groups based on the specific technology. In addition, to allow for technologies present on the Basic Engine and Dynamic Road Load (DLR) (i.e., MR, AERO, and ROLL) paths to be evaluated and applied in any given combination, we established a unique group for each of these technologies.

As such, the following technology groups are defined within the modeling system: engine cam configuration (CONFIG), VVL engine technology, SGDI engine technology, cylinder deactivation, non-basic engine technologies (ADVENG), TRANS, electrification (ELEC), low rolling resistance tires (ROLL), aerodynamic improvements (AERO), and MR levels. The combination of technologies along each of these groups forms a unique technology state vector and defines a unique technology combination that corresponds to a single point in the database for each technology class evaluated within the modeling system. This technology state vector is commonly referred to as a 'technology key' or 'tech key' in this analysis.

As an example, a technology state vector describing a vehicle with a SOHC engine, VVT (only), an AT6, a belt-integrated starter generator, rolling resistance (level 1), aerodynamic improvements (level 2), MR (level 1), electric power steering, and low drag brakes, is specified as "SOHC; VVT; ; ; ; ; AT6; BISG; ROLL10; AERO20; MR1."[182] By assigning each unique technology combination a tech key such as the one in the example, the CAFE Model can identify the initial technology state of each vehicle in the analysis fleet and map it to a point (unique technology combination) in the database.

Once a vehicle is assigned (or mapped) to an appropriate technology state vector (from one of approximately three million unique combinations, which are defined in the vehicle simulation database as CONFIG; VVT; VVL; SGDI; DEAC; ADVENG; TRANS; ELEC; ROLL; AERO; MR), adding a new technology to the vehicle represents progress from a previous state vector to a new state vector. The previous state vector simply refers to the technologies that are currently in use on a vehicle. The new state vector, however, is computed within the modeling system by adding a new technology to the combination of technologies represented by the previous state vector, while simultaneously removing any other technologies that are superseded by the newly added one.

For example, consider the vehicle with the state vector described as: SOHC; VVT; AT6; Belt Integrated Starter Generator (BISG); ROLL10; AERO20; MR1. Assume the system is evaluating PHEV20 as a

[181] See, e.g., 2015 NAS Report, at 18. Fuel consumption is the volume of fuel consumed divided by the distance traveled, and is the inverse of fuel economy, which is distance traveled divided by the volume of fuel used, usually reported in mpg.

[182] In the example technology state vector, the series of semicolons between VVT and AT6 correspond to the engine technologies that are not included as part of the combination. The extra semicolons for omitted technologies are preserved in this example for clarity and emphasis, and will not be included in future examples.

candidate technology for application on this vehicle. The new tech state vector for this vehicle is computed by removing SOHC, VVT, AT6, and BISG technologies from the previous state vector,[183] while also adding PHEV20, resulting in the following: PHEV20; ROLL10; AERO20; MR1.

From here, it is relatively simple to obtain a fuel economy improvement factor for any new combination of technologies and apply that factor to the fuel economy of a vehicle in the analysis fleet. The formula for calculating a vehicle's fuel economy after application of each successive technology represented within the database is defined as the ratio of the fuel economy improvement factor associated with the technology state vector before application of a candidate technology and after the application of a candidate technology.[184] The resulting improvement is applied to the original compliance fuel economy value for a discrete vehicle in the analysis fleet, as discussed previously in this chapter.

2.3.7. Compliance and Real-World Fuel Economy "Gap"

The statutorily mandated vehicle fuel economy test cycles for NHTSA's CAFE program compliance consist of two separate test cycles, the "city" and "highway" cycles, commonly referred to as the 2-cycle tests. In 2008, EPA introduced three additional test cycles to bring "label" values from two-cycle testing in line with efficiency values consumers were experiencing in the real world, particularly for hybrids. This is known as 5-cycle testing.

Generally, the revised 5-cycle testing values have proven to be a good approximation of what consumers will experience during vehicle operation, significantly better than the previous 2-cycle test values.

The CAFE regulatory analysis utilizes "on-road" fuel economy values, which are the ratio of 5-cycle to 2-cycle testing values, i.e., the CAFE compliance values to the "label" values.

For this analysis, DOT applied a certain percent difference between the 2-cycle test and 5-cycle test to represent the gap in compliance fuel economy and real-world fuel economy.[185] This percent difference, or "gap", is calculated as shown in Equation 2-5.

Equation 2-5: Percent Difference Between 2-Cycle and 5-Cycle Tests

$$\frac{2cycleFE\text{-}5cycleFE}{2cycleFE}*100=\text{"fuel economy gap" } (\%)$$

Table 2-23 below shows a summary of the inputs used for the fuel economy gap for different fuel types.[186] The underlying data for this is EPA test data.[187] These data are average fleet-wide values; in reality the true fuel economy gap will be lower for some vehicles and higher for other vehicles.

Table 2-23: 2-Cycle to 5-Cycle "Gap" Used for This Analysis, by Fuel Type

	Cars	Vans/SUVs/LTs
Gasoline	24%	24%
Ethanol-85	24%	24%
Diesel	24%	24%
Electricity	29%	29%
Hydrogen	29%	29%
Compressed Natural Gas	24%	24%

[183] For more discussion of how the CAFE Model handles technology supersession, see S4.5 of the CAFE Model Documentation.
[184] For more discussion of how the CAFE Model calculates a vehicle's fuel economy where the vehicle switches from one type of fuel to another, for example, from gasoline operation to diesel operation or from gasoline operation to plug-in hybrid/electric vehicle operation, see S4.6 of the CAFE Model Documentation.
[185] For more details see the CAFE Model Documentation.
[186] This input is specific in the Parameters Input File.
[187] EPA. Download Fuel Economy Data. Available at: https://www.fueleconomy.gov/feg/download.shtml. (Accessed: Dec. 21, 2023).

We also use the same "gap" assumptions for the HDPUV analysis.

2.4. Technology Costs

We estimate present and future costs for fuel-saving technologies by taking into consideration the type of vehicle, or type of engine when technology costs vary by application. These cost estimates are based on three main inputs. First, direct manufacturing costs (DMCs) or the component and labor costs of producing and assembling the physical parts and systems, are estimated assuming high volume production. Second, we estimate indirect costs. DMCs generally do not include the indirect costs of tools, capital equipment, financing, engineering, sales, administrative support, or return on investment. We account for these indirect costs via a scalar markup of direct manufacturing costs (the retail price equivalent [RPE]). Finally, the costs for technologies may change over time as industry streamlines design and manufacturing processes. To model this, we estimate potential cost improvements with cost learning (CL). The retail cost of equipment in any future year is estimated to be equal to the product of the DMC, RPE, and CL. Considering the retail cost of equipment, instead of merely direct manufacturing costs, is important to account for the real-world price effects of a technology, as well as market realities.

2.4.1. Direct Manufacturing Costs

DMCs are the component and assembly costs of the physical parts and systems that make up a complete vehicle. The analysis uses agency-sponsored tear-down studies of vehicles and parts to estimate the DMCs of individual technologies, in addition to independent tear-down studies, other publications, and CBI. In the simplest cases, the agency-sponsored studies produced results that confirmed third-party industry estimates and aligned with confidential information provided by manufacturers and suppliers. In cases with a large difference between the tear-down study results and credible independent sources, we scrutinized the study assumptions, and sometimes revised or updated the analysis accordingly.

Due to the variety of technologies and their applications, and the cost and time required to conduct detailed tear-down analyses, the agency did not sponsor teardown studies for every technology. In addition, the analysis includes some fuel-saving technologies that are pre-production or sold in very small pilot volumes. For those technologies, we could not conduct a tear-down study to assess costs because the product is not yet in the marketplace for evaluation. In these cases, we rely upon third-party estimates and confidential information from suppliers and manufacturers; however, there are some common pitfalls with relying on CBI to estimate costs. The agency and the source may have had incongruent or incompatible definitions of the reference point from which to measure costs. The source may have provided DMCs at a date many years in the future, and assumed very high production volumes, important caveats to consider for agency analysis. In addition, a source may provide incomplete and/or misleading information. In other cases, intellectual property considerations and strategic business partnerships may have contributed to a manufacturer's cost information and could be difficult to account for in the CAFE Model as not all manufacturers may have access to proprietary technologies at stated costs. We carefully evaluate new information in light of these common pitfalls, especially regarding emerging technologies.

While costs for fuel-saving technologies reflect the best estimates available today, technology cost estimates will likely change in the future as technologies are deployed and as production is expanded, and as nascent technologies mature. For emerging technologies, we use the best information available at the time of the analysis and will continue to update cost assumptions for any future analysis. Chapter 3 discusses each category of technologies (e.g., engines, transmissions, electrification) and the cost estimates we use for this analysis.

2.4.2. Indirect Costs (Retail Price Equivalent)

As discussed above, direct costs represent the cost associated with acquiring raw materials, fabricating parts, and assembling vehicles with the various technologies manufacturers are expected to use to meet future CAFE standards. They include materials, labor, and variable energy costs required to produce and assemble the vehicle. However, they do not include overhead costs required to develop and produce the vehicle, costs incurred by manufacturers or dealers to sell vehicles, or the profit manufacturers and dealers make from their investments. These items together contribute to the price consumers ultimately pay for the vehicle. Table 2-24 illustrates how these components can affect retail prices.

Table 2-24: Retail Price Components

Direct Costs	
Manufacturing Cost	Cost of materials, labor, and variable energy needed for production
Indirect Costs	
Production Overhead	
Warranty	Cost of providing product warranty
Research and Development	Cost of developing and engineering the product
Depreciation and amortization	Depreciation and amortization of manufacturing facilities and equipment
Maintenance, repair, operations	Cost of maintaining and operating manufacturing facilities and equipment
Corporate Overhead	
General and Administrative	Salaries of nonmanufacturing labor, operations of corporate offices, etc.
Retirement	Cost of pensions for nonmanufacturing labor
Health Care	Cost of health care for nonmanufacturing labor
Selling Costs	
Transportation	Cost of transporting manufactured goods
Marketing	Manufacturer costs of advertising manufactured goods
Dealer Costs	
Dealer selling expense	Dealer selling and advertising expense
Dealer profit	Net Income to dealers from sales of new vehicles
Net income	Net income to manufacturers from production and sales of new vehicles

To estimate the impact of higher vehicle prices on consumers, we must consider both direct and indirect costs. To estimate total consumer costs, we multiply direct manufacturing costs by an indirect cost factor to represent the average price for fuel-saving technologies at retail.

Historically, the most common method used to estimate indirect costs of producing a motor vehicle has been the RPE. The RPE markup factor is based on an examination of historical financial data contained in 10-K reports filed by manufacturers with the Securities and Exchange Commission. It represents the ratio between the retail price of motor vehicles and the direct costs of all activities that manufacturers engage in.

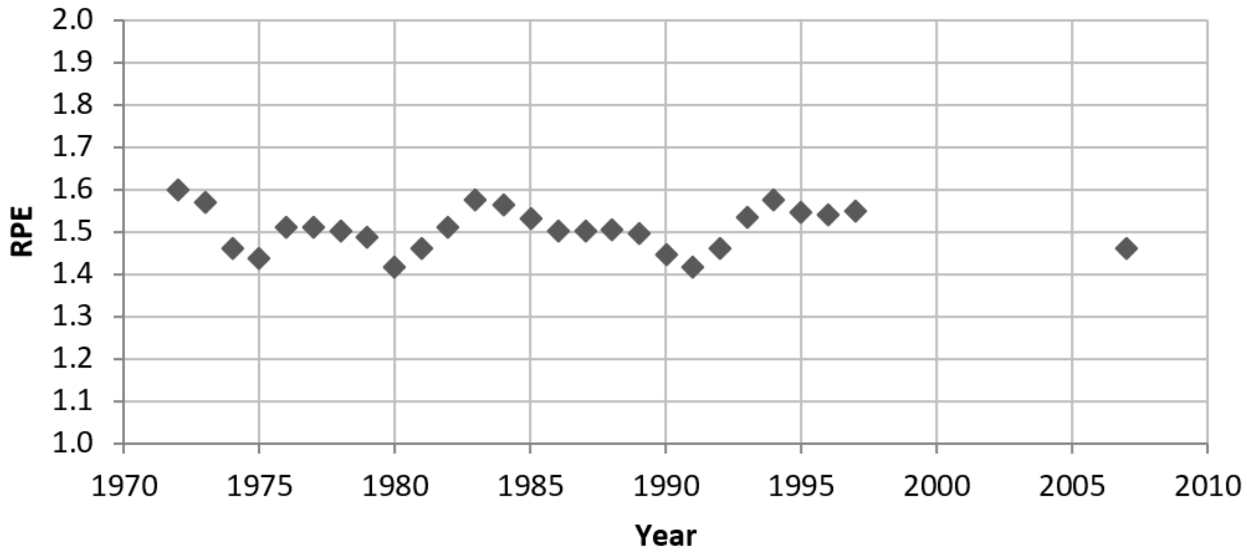
Figure 2-8 indicates that for more than three decades, the retail price of motor vehicles has been, on average, roughly 50 percent above the direct cost expenditures of manufacturers. This ratio has been remarkably consistent, averaging roughly 1.5 with minor variations from year to year over this period. At no point has the RPE markup exceeded 1.6 or fallen below 1.4.[188] During this time frame, the average annual increase in real

[188] Based on data from 1972-1997 and 2007. Data were not available for intervening years, but results for 2007 seem to indicate no significant change in the historical trend.

direct costs was 2.5 percent, and the average annual increase in real indirect costs was also 2.5 percent. Figure 2-8 illustrates the historical relationship between retail prices and direct manufacturing costs.[189]

An RPE of 1.5 does not imply that manufacturers automatically mark up each vehicle by exactly 50 percent. Rather, it means that, over time, the competitive marketplace has resulted in pricing structures that average out to this relationship across the entire industry. Prices for any individual model may be marked up at a higher or lower rate depending on market demand. The consumer who buys a popular vehicle may, in effect, subsidize the installation of a new technology in a less marketable vehicle. But, on average, over time and across the vehicle fleet, the retail price paid by consumers has risen by about $1.50 for each dollar of direct costs incurred by manufacturers.

Figure 2-8: Historical Data for Retail Price Equivalent (RPE), 1972-1997 and 2007



It is also important to note that direct costs associated with any specific technology will change over time as some combination of learning and resource price changes occurs. Resource costs, such as the price of steel, can fluctuate over time and can experience real long-term trends in either direction, depending on supply and demand. However, the normal learning process generally reduces direct production costs as manufacturers refine production techniques and seek out less costly parts and materials for increasing production volumes. By contrast, this learning process does not generally influence indirect costs. The implied RPE for any given technology would thus be expected to grow over time as direct costs decline relative to indirect costs. The RPE for any given year is based on direct costs of technologies at different stages in their learning cycles, and that may have different implied RPEs than they did in previous years. The RPE averages 1.5 across the lifetime of technologies of all ages, with a lower average in earlier years of a technology's life, and, because of learning effects on direct costs, a higher average in later years.

NHTSA has used RPE in all previous safety rulemakings and most previous CAFE rulemakings to estimate costs. In 2011 the NAS recommended RPEs of 1.5 for suppliers and 2.0 for in-house production be used to estimate total costs.[190] The former Alliance of Automobile Manufacturers also advocated these values as appropriate markup factors for estimating costs of technology changes.[191] In their 2015 report, the NAS

[189] Rogozhin, A. et al. 2009. Automobile Industry Retail Price Equivalent and Indirect Cost Multipliers. Report by RTI International to Office of Transportation Air Quality. U.S. Environmental Protection Agency. RTI Project Number 0211577.002.004. Feb. 2009. Research Triangle Park, N.C.; Spinney, B.C. 1999. Advanced Air Bag Systems Cost, Weight, and Lead Time Analysis Summary Report. Contract NO. DTNH22-96-0-12003, Task Orders – 001, 003, and 005. U.S. Department of Transportation. Washington, D.C.
[190] Transportation Research Board and National Research Council. 2002. Effectiveness and Impact of Corporate Average Fuel Economy Standards. NRC. *The National Academies Press*: Washington, D.C. Available at: https://nap.nationalacademies.org/catalog/10172/effectiveness-and-impact-of-corporate-average-fuel-economy-cafe-standards. (Accessed: May 31, 2023).
[191] Communication from Chris Nevers (Alliance) to Christopher Lieske (EPA) and James Tamm (NHTSA) VIA Regulations.gov http://www.regulations.gov Docket ID Nos. NHTSA-2018-0067; EPA-HQ-OAR-2018-0283, p. 143.

recommend 1.5 as an overall RPE markup.[192] An RPE of 2.0 has also been adopted by a coalition of environmental and research groups (Northeast States Center for a Clean Air Future [NESCCAF], ICCT, SwRI, and TIAX-LLC) in a report on reducing heavy truck emissions, and 2.0 is recommended by the U.S. Department of Energy for estimating the cost of hybrid-electric and automotive fuel cell costs (see Vyas et al. (2000) in Table 2-25 below). Table 2-25 below also lists other estimates of the RPE. Note that all RPE estimates vary between 1.4 and 2.0, with most in the 1.4 to 1.7 range.

Table 2-25: Alternate Estimates of the RPE[193]

Author and Year	Value, Comments
Jack Faucett Associates for EPA, 1985	1.26 initial value, later corrected to 1.7+ by Sierra research
Vyas et al., 2000	1.5 for outsourced, 2.0 for OEM, electric, and hybrid vehicles
NRC, 2002	1.4 (corrected to > by Duleep)
McKinsey and Company, 2003	1.7 based on European study
CARB, 2004	1.4 (derived using the Jack Faucett Associates initial 1.26 value, not the corrected 1.7+ value)
Sierra Research for American Automobile Association (AAA), 2007	2.0 or >, based on Chrysler data
Duleep, 2008	1.4, 1.56, 1.7 based on integration complexity
NRC, NAS 2011	1.5 for Tier 1 supplier, 2.0 for OEM
NRC, NAS 2015	1.5 for OEM

The RPE has thus enjoyed widespread use and acceptance by a variety of governmental, academic, and industry organizations.

As in previous CAFE and safety rulemaking analyses, we relied on the RPE to account for indirect manufacturing costs. The RPE accounts for indirect costs like engineering, sales, and administrative support, as well as other overhead costs, business expenses, warranty costs, and return on capital considerations.

[192] National Academies of Sciences, Engineering, and Medicine. 2011. Assessment of Fuel Economy Technologies for Light Duty Vehicles. *The National Academies Press:* Washington, D.C. Available at: https://nap.nationalacademies.org/catalog/12924/assessment-of-fuel-economy-technologies-for-light-duty-vehicles. (Accessed: May 31, 2023); National Academies of Sciences, Engineering, and Medicine. 2015. Cost, Effectiveness, and Deployment of Fuel Economy Technologies in Light Duty Vehicles. *The National Academies Press*: Washington, D.C. Available at: https://nap.nationalacademies.org/catalog/21744/cost-effectiveness-and-deployment-of-fuel-economy-technologies-for-light-duty-vehicles. (Accessed: May 31, 2023).

[193] Duleep, K.G. 2008. Analysis of Technology Cost and Retail Price. Presentation to Committee on Assessment of Technologies for Improving Light-Duty Vehicle Fuel Economy. Jan. 25, 2008. Detroit, Mich. as cited in National Academies of Sciences, Engineering, and Medicine. 2011. Assessment of Fuel Economy Technologies for Light Duty Vehicles. *The National Academies Press:* Washington, D.C. Available at: https://nap.nationalacademies.org/catalog/12924/assessment-of-fuel-economy-technologies-for-light-duty-vehicles. (Accessed: May 31, 2023); Jack Faucett Associates. 1985. Update of EPA's Motor Vehicle Emission Control Equipment Retail Price Equivalent (RPE) Calculation Formula. Final Report. No. 68-03-3244. EPA. Available at: https://nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=940047LI.txt. (Accessed: May 31, 2023); McKinsey & Company. 2003. Preface to the Auto Sector Cases. *New Horizons - Multinational Company Investment in Developing Economies*. Mckinsey Global Institute: San Francisco, CA. Available at: https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/McKinsey%20Digital/Our%20Insights/New%20horizons%20for%20multinational%20company%20investment/MGI_Multinational_company_investment_in_developing_economies_Full_Report.ashx.; NRC. 2002. Effectiveness and Impact of Corporate Average Fuel Economy Standards. *The National Academies Press:* Washington, D.C.; NRC. 2011. Assessment of Fuel Economy Technologies for Light Duty Vehicles. *The National Academies Press:* Washington, D.C.; NRC. 2015. Cost, Effectiveness, and Deployment of Fuel Economy Technologies in Light Duty Vehicles. *The National Academies Press:* Washington, D.C.; Sierra Research, Inc. 2007. Study of Industry-Average Mark-Up Factors used to Estimate Changes in Retail Price Equivalent (RPE) for Automotive Fuel Economy and Emissions Control Systems. Sierra Research, Inc.: Sacramento, CA -; Vyas, A. et al. 2000. Comparison of Indirect Cost Multipliers for Vehicle Manufacturing. Center for Transportation Research. ANL: Argonne, Ill. Available at: https://publications.anl.gov/anlpubs/2000/05/36074.pdf.

In past rulemakings a second type of indirect cost multiplier has also been examined, known as the "indirect cost multiplier" (ICM) approach. ICMs were first examined alongside the RPE approach in the 2010 rulemaking regarding standards for model years 2012-2016. Both methods have been examined in subsequent rulemakings. We continue to employ the RPE approach as a cost multiplier for this analysis. A detailed discussion of indirect cost methods and the basis for our use of the RPE to reflect these costs is available in the Final Regulatory Impact Analysis (FRIA) for the 2020 Safer Affordable Fuel-Efficient (SAFE) rule.[194]

2.4.3. Cost Learning

Manufacturers make improvements to production processes over time, which often result in lower costs. "Cost learning" reflects the effect of experience and volume on the cost of production, which generally results in better utilization of resources, leading to higher and more efficient production. As manufacturers gain experience through production, they refine production techniques, raw material and component sources, and assembly methods to maximize efficiency and reduce production costs. Typically, a representation of this cost learning, or learning curves, reflect initial learning rates that are relatively high, followed by slower learning as additional improvements are made and production efficiency peaks. This eventually produces an asymptotic shape to the learning curve, as small percent decreases are applied to gradually declining cost levels. These learning curve estimates are applied to various technologies that are used to meet CAFE standards.

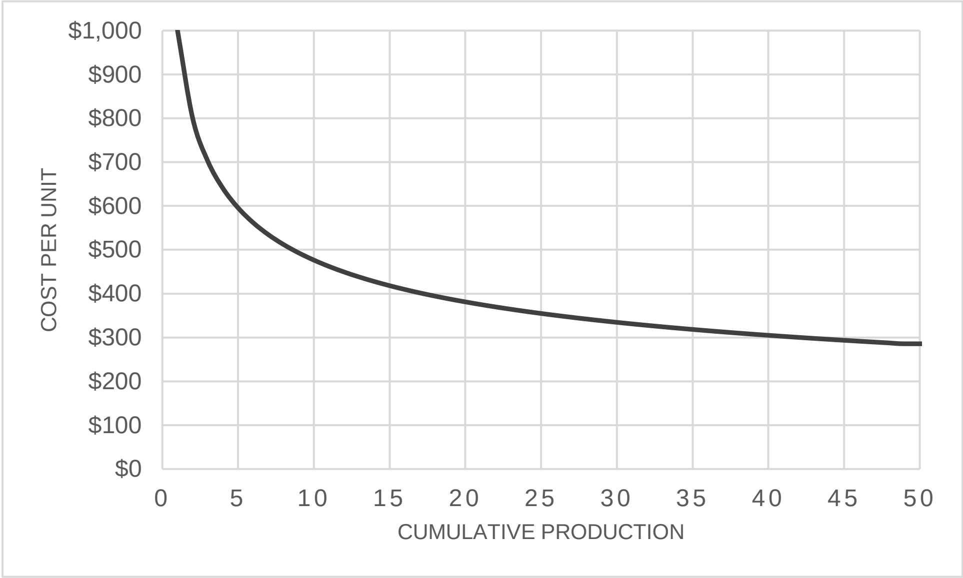
Although the concept of a learning curve was initially developed to describe cost reduction due to improvements in manufacturing processes due to knowledge gained through experience in production, it has since been recognized that other factors make important contributions to cost reductions associated with cumulative production.[195] Sixty years ago, Arrow noted that learning by doing was the acquisition of knowledge that increased productivity and included technological progress.[196] In a review of experience curves for power plant emission controls, Rubin et al. noted that learning curves (also known as "experience curves") reflected not only the benefits of process learning but investments in research and development, as well.[197] Clarke et al. also observed that empirically estimated learning curves can include both technological changes and scale economies.[198]

NHTSA estimated CL by considering methods established by T.P. Wright and later expanded upon by J.R. Crawford. Wright, examining aircraft production, found that every doubling of cumulative production of airplanes resulted in decreasing labor hours at a fixed percentage. This fixed percentage is commonly referred to as the progress rate or progress ratio, where a lower rate implies faster learning as cumulative production increases. J.R. Crawford expanded upon Wright's learning curve theory to develop a single unit cost model, that estimates the cost of the nth unit produced given the following information is known: (1) cost to produce the first unit; (2) cumulative production of n units; and (3) the progress ratio.

As pictured in Figure 2-9, Wright's learning curve shows the first unit is produced at a cost of $1,000. Initially cost per unit falls rapidly for each successive unit produced. However, as production continues, cost falls more gradually at a decreasing rate. For each doubling of cumulative production at any level, cost per unit declines 20 percent, so that 80 percent of cost is retained. The majority of technologies in the CAFE Model use the basic approach by Wright, where cost reduction is estimated by applying a fixed percentage to the projected cumulative production of a given fuel economy technology.

[194] EPA and NHTSA. 2020. The Safer Affordable Fuel-Efficient (SAFE) Vehicles Final Rule for Model Year 2021-2026 Passenger Cars and Light Trucks. Final Regulatory Impact Analysis. Environmental Protection Agency and Department of Transportation. Washington, D.C. pp 354-76. Available at: https://www.govinfo.gov/content/pkg/FR-2020-04-30/pdf/2020-06967.pdf. (Accessed: Apr. 3, 2024).
[195] Wene, C.O. 2000. Experience Curves for Energy Technology Policy. International Energy Agency, OECD. Paris. Available at: https://www.oecd-ilibrary.org/energy/experience-curves-for-energy-technology-policy_9789264182165-en. (Accessed: May 31, 2023).
[196] Arrow, K. 1962. The Economic Implications of Learning by Doing. *Review of Economic Studies*. Vol. 29(3): pp. 155-73. Available at: https://www.jstor.org/stable/2295952. (Accessed May 31, 2023).
[197] Rubin, E. et al. 2004. Experience Curves for Power Plant Emission Control Technologies. *International Journal of Energy Technology and Policy.* Vol. 2(1/2): pp. 52-69. Available at: https://escholarship.org/uc/item/503543gq. (accessed: May 31, 2023).
[198] Clarke, L. et al. 2006. On the Sources of Technological Change: Assessing the Evidence. *Energy Economics*. Vol. 28(5-6): pp. 579-95. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0140988306000569. (Accessed: May 31, 2023).

Figure 2-9: Wright's Learning Curve (Progress Ratio = 0.8)



The analysis accounts for learning effects with model year-based CL forecasts for each technology that reduce direct manufacturing costs over time. NHTSA evaluated the historical use of technologies, and reviewed industry forecasts to estimate future volumes for the purpose of developing the model year-based technology CL curves.

The following subchapter discusses NHTSA's development of model year-based CL forecasts, including how the approach has evolved from the 2012 light vehicle rulemaking, and how the progress ratios were developed for different technologies considered in the analysis. Finally, we discuss how these learning effects are applied in the CAFE Model.

2.4.3.1. Time Versus Volume-Based Learning

For the 2012 joint CAFE/CO_2 rulemaking, NHTSA developed learning curves as a function of vehicle model year. Although the concept of this methodology is derived from Wright's cumulative production volume-based learning curve, its application for CAFE and CO_2 technologies was more of a function of time. More than a dozen learning curves schedules were developed, varying between fast and slow learning, and assigned to each technology corresponding to its level of complexity and maturity. The schedules were applied to the base year of direct manufacturing cost and incorporate a percentage of cost reduction by model year declining at a decreasing rate through the technology's production life. Some newer technologies experience 20 percent cost reductions for introductory model years, while mature or less complex technologies experience 0-3 percent cost reductions over a few years.

In their 2015 report to Congress, the NAS recommended that NHTSA should "continue to conduct and review empirical evidence for the cost reductions that occur in the automobile industry with volume, especially for large-volume technologies that will be relied on to meet the CAFE/GHG standards."

In response, we have incorporated statically projected cumulative volume production data of fuel economy-improving technologies, representing an improvement over the previously used time-based method. Dynamic projections of cumulative production are not feasible with current CAFE model capabilities, so one set of projected cumulative production data for most vehicle technologies was developed for the purpose of determining cost impact. For many technologies produced and/or sold in the U.S., historical cumulative production data was obtained to establish a starting point for learning curves. Groups of similar technologies or technologies of similar complexity may share identical learning curves.

The slope of the learning curve, which determines the rate at which cost reductions occur, has been estimated using research from an extensive literature review and automotive cost tear-down reports (see below). The slope of the learning curve is derived from the progress ratio of manufacturing automotive and other mobile source technologies.

2.4.3.2. Deriving the Progress Ratio Used in this Analysis

Learning curves vary among different types of manufactured products. Progress ratios can range from 70 to 100 percent, where 100 percent indicates no learning can be achieved. Learning effects tend to be greatest in operations where workers often touch the product, while effects are less substantial in operations consisting of more automated processes. As automotive manufacturing plant processes become increasingly automated, a progress ratio towards the higher end would seem more suitable. NHTSA incorporated findings from automotive cost-teardown studies with EPA's literature review of learning-related studies to estimate a progress ratio used to determine learning schedules of fuel economy-improving technologies.

EPA's literature review examined and summarized 20 studies related to learning in manufacturing industries and mobile source manufacturing. The studies focused on many industries, including motor vehicles, ships, aviation, semiconductors, and environmental energy. Based on several criteria, EPA selected five studies providing quantitative analysis from the mobile source sector (progress ratio estimates from each study are summarized in Table 2-26, below). Further, those studies expand on Wright's Learning Curve function by using cumulative output as a predictor variable, and unit cost as the response variable. As a result, EPA determined a best estimate of 84 percent as the progress ratio in mobile source industries. However, of those five studies, EPA at the time placed less weight on the Epple et al. (1991) study, because of a disruption in learning due to incomplete knowledge transfer from the first shift to introduction of a second shift at a North American truck plant. While learning may have decelerated immediately after adding a second shift, we note that unit costs continued to fall as the organization gained experience operating with both shifts. NHTSA now recognizes that disruptions are an essential part of the learning process and should not, in and of themselves, be discredited. For this reason, the analysis uses a re-estimated average progress ratio of 85 percent from those five studies (equally weighted).

Table 2-26: Progress Ratios from EPA's Literature Review

Author (Publication Date)	Industry	Progress Ratio (Cumulative Output Approach)
Argote et al. (1997) as cited in Argote (2013)[199]	Trucks	85%
Benkard (2000)[200]	Aircraft (commercial)	82%
Epple et al. (1991)[201]	Trucks	90%
Epple et al. (1996)[202]	Trucks	85%
Levitt et al. (2013)[203]	Automobiles	82%

In addition to EPA's literature review, this progress ratio estimate was informed based on NHTSA's findings from automotive cost-teardown studies. NHTSA routinely performs evaluations of costs of previously issued FMVSS for new motor vehicles and equipment. NHTSA's engages contractors to perform detailed engineering "tear-down" analyses for representative samples of vehicles, to estimate how much specific FMVSS add to the weight and retail price of a vehicle. As part of the effort, cost and production volume are

[199] Argote, L. 2013. Organizational Learning: Creating, Retaining and Transferring Knowledge. Springer: New York, NY. Available at: https://doi.org/10.1007/978-1-4614-5251-5. (Accessed: May 31, 2023).
[200] Benkard, C. L. 2000. Learning and Forgetting: the Dynamics of Aircraft Production. *The American Economic Review*. Vol. 90(4): pp. 1034–54. Available at: https://www.jstor.org/stable/117324. (Accessed: Apr. 3, 2024).
[201] Epple, D. et al. 1991 Organizational Learning Curves - A Method for Investigating Intra-Plant Transfer of Knowledge Acquired through Learning by Doing, *Organization Science.* Vol. 2(1): pp. 58–70. Available at: https://www.jstor.org/stable/2634939. (Accessed: Apr. 3, 2024).
[202] Epple, D. et al. 1996. An Empirical Investigation of the Microstructure of Knowledge Acquisition and Transfer through Learning by Doing. *Operations Research.* Vol. 44(1): pp. 77–86. Available at: https://pubsonline.informs.org/doi/10.1287/opre.44.1.77. (Accessed: Apr. 3, 2024).
[203] Levitt, S. D. et al. 2013. Toward an Understanding of Learning by Doing - Evidence from an Automobile Assembly Plant. Journal of Political Economy. Vol. 121(4): pp. 643-81. Available at: https://www.nber.org/papers/w18017. (Accessed: Apr. 3, 2024).

examined for automotive safety technologies. In particular, NHTSA estimated costs from multiple cost tear-down studies for technologies with actual production data from the cost and weight added by the Federal Motor Vehicle Safety Standards for model year 1968-2012 passenger cars and LTVs (2017).

NHTSA chose five vehicle safety technologies with sufficient data to estimate progress ratios of each, because these technologies are large-volume technologies and are used by almost all vehicle manufacturers. Table 2-27 below includes these five technologies and yields an average progress rate of 92 percent:

Table 2-27: Progress Ratios Researched by NHTSA

Technology	Progress Ratio
Anti-lock Brake Systems	87%
Driver Airbags	93%
Manual 3-pt lap shoulder safety belts	96%
Adjustable Head Restraints	91%
Dual Master Cylinder	95%

For a final progress ratio used in the CAFE Model, the five progress rates from EPA's literature review and five progress rates from NHTSA's evaluation of automotive safety technologies results were averaged. This resulted in an average progress rate of approximately 89 percent. Equal weight was placed on progress ratios from all 10 sources. More specifically, equal weight was placed on the Epple et al. (1991) study, because disruptions have more recently been recognized as an essential part in the learning process, especially to increase the rate of output.

2.4.3.3. Obtaining Appropriate Reference Years for Direct Manufacturing Costs to Create Learning Curves

Direct manufacturing costs for each fuel economy-improving technology were obtained from various sources, as discussed above. To establish a consistent basis for direct manufacturing costs in the rulemaking analysis, each technology cost is adjusted to 2021 dollars. For each technology, the DMC is associated with a specific model year, and sometimes a specific production volume, or cumulative production volume. The base model year is established as the model year in which direct manufacturing costs were assessed (with learning factor of 1.00). With the data on cumulative production volume for each technology and the assumption of a 0.89 progress ratio for all automotive technologies, we can solve for an implied cost for the first unit produced. For some technologies, we used modestly different progress ratios to match detailed cost projections if available from another source (for instance, batteries for plug-in hybrids and BEVs).

This approach produced reasonable estimates for technologies already in production, and some additional steps were required to set appropriate learning curves for technologies not yet in production. For pre-production cost estimates in previous CAFE rulemakings, NHTSA often relied on CBI sources to predict future costs. Many sources for pre-production cost estimates include significant learning effects, often providing cost estimates assuming high volume production, and often for a timeframe late in the first production generation or early in the second generation of the technology. Rapid doubling and re-doubling of a low cumulative volume base with Wright's learning curves can provide unrealistic cost estimates. In addition, direct manufacturing cost projections can vary depending on the initial production volume assumed. Accordingly, we carefully examined direct costs with learning, and adjusted the starting point for those technologies on the learning curve to better align with the assumptions used for the initial direct cost estimate.

2.4.4. Cost Learning as Applied in the CAFE Model

For this analysis, we apply learning effects to the incremental cost over the null technology state on the applicable technology tree. After this step, we calculate year-by-year incremental costs over preceding technologies on the technology tree to create the CAFE Model inputs. The shift from incremental cost accounting to absolute cost accounting in recent CAFE analyses made cost inputs more transparently relatable to detailed model output, and relevant to this discussion, made it easier to apply learning curves while developing inputs to the CAFE Model.

We grouped certain technologies – such as some advanced transmissions and non-battery electrified vehicle components – and assigned them to the same learning schedule. In addition, we assigned advanced engine technologies that are based on a singular preceding technology to the same learning curve as that preceding technology. While the grouped technologies differ in operating characteristics and design, we chose to group them based on their complexity, technology integration, and economies of scale across manufacturers. The low volume of certain advanced technologies – such as hybrid-electric and pure-electric powertrain technologies – poses a significant issue for suppliers and prevents them from producing components needed for advanced transmissions and other technologies at more efficient high scale production. The technology groupings consider market availability, complexity of technology integration, and production volume of the technologies that can be implemented by manufacturers and suppliers.

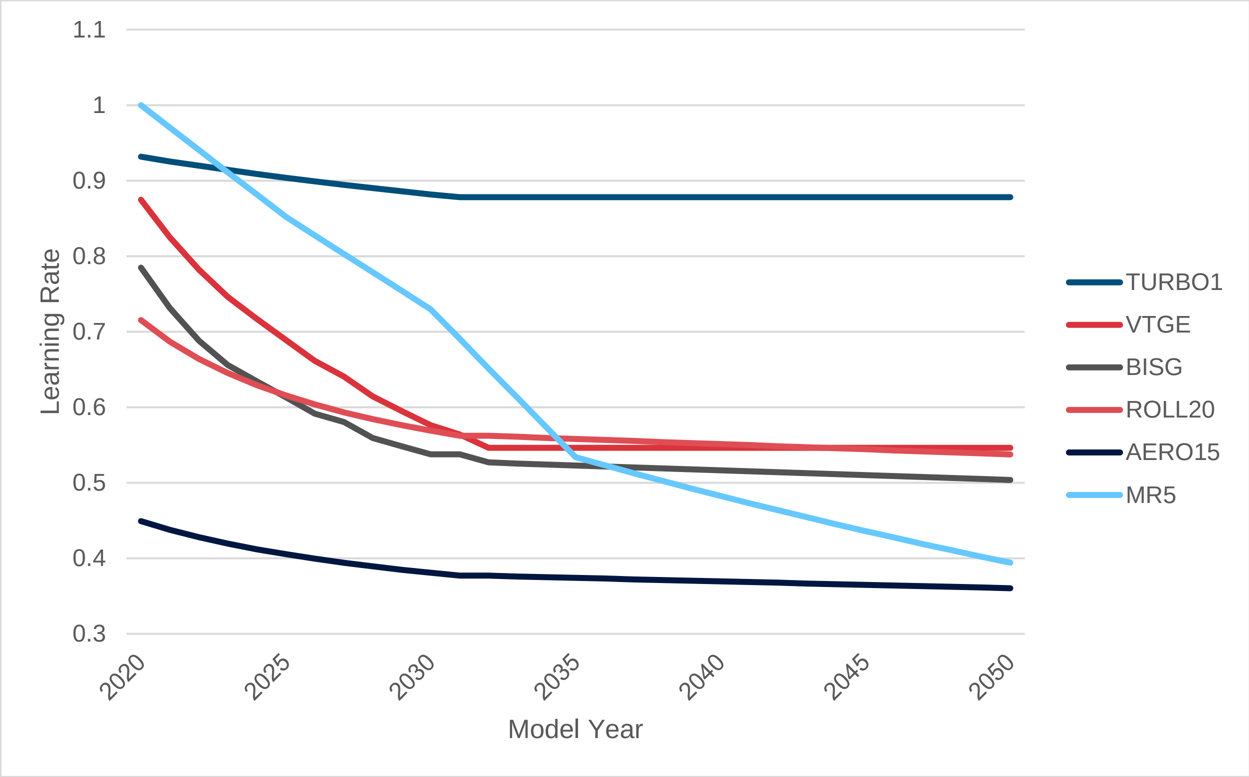
Both light-duty and HDPUV technologies have the same learning rates. Although most HDPUV components will have higher operating loads and provide different effectiveness values than light-duty components, the overall designs are similar between light-duty and HDPUV technologies. This approach was used for the HD Phase 2 analysis for HDPUVs[204] and we think that this is an appropriate assumption to continue to use for this analysis. The individual technology design and effectiveness differences between light-duty and HDPUV technologies are discussed in Chapter 3.

We set model inputs for the explicit simulation of technology application from model year 2020 through model year 2050. Accordingly, we updated the learning curves for each technology group to cover those same model years. For model years 2020-2036, we expect incremental improvements in nearly all technologies, particularly in electrification technologies because of increased production volumes, labor efficiency, improved manufacturing methods, specialization, network building, and other factors; this contributes to continual cost learning, and we believe that many fuel economy-improving technologies considered in this rule will approach a flat learning level by model year 2036. Older and less complex ICE and TRANS will reach a flattened learning curve sooner when compared to electrification technologies, which have more opportunity for improvement. For SS12V batteries and non-battery electrification components, we estimate steeper learning curves beginning with model year 2020; we estimate that the learning curve for non-battery electrification components will gradually flatten after model year 2032, while the learning curve for SS12V batteries will continue to decrease for model years 2032-2050, although, at a shallower rate. We estimate that learning curves for high-voltage battery packs – used in highly electrified vehicles – will sharply decrease between model years 2020-2022, flatten between model years 2022-2025, and then continue to steadily decrease for model years 2026-2050. For more detailed discussions of the non-battery electrification, battery electrification, and non-electrification learning curves, see Chapter 3.3.5.3.2, Chapter 3.3.5.3.1, and Chapter 2.4.4.1, respectively.

Each technology in the CAFE Model is assigned a learning schedule developed from the methodology explained previously. For example, the following chart Figure 2-10 shows learning curves for several technologies applicable to midsize sedans – demonstrating that while we estimate that such learning effects have already been almost entirely realized for engine turbocharging (a technology that has been in production for many years), we estimate that significant opportunities to reduce the cost of the greatest levels of mass reduction (e.g., MR5) and even greater opportunities to reduce the cost of electrified vehicle batteries still remain. In fact, for certain advanced technologies, we determined that the results predicted by the standard learning curves progress ratio, based on unusual market price and production relationships, were not realistic. For these technologies, we developed specific learning estimates that may diverge from the 0.89 progress rate. As shown in Figure 2-10, these technologies include: turbocharging and downsizing level 1 (TURBO1), electrically-variable turbo geometry (VTGE), aerodynamic drag reduction by 15 percent (AERO15), mass reduction level 5 (MR5), 20 percent improvement in low-rolling resistance tire technology (ROLL20), and belt integrated starter/generator (BISG).

[204] MDHD Phase 2 FRIA at 2-56.

Figure 2-10: Examples of Learning Curves for CAFE Model Technologies



2.4.4.1. Non-Electrification Technology Learning Curves

When analyzing the learning curves for conventional vehicle technologies, we group them into one of four categories: 1) basic engine technologies, 2) advanced engine technologies, 3) transmission technologies, and 4) rolling resistance technologies. We consider the two base engine technologies (i.e., SOHC and DOHC) to be mature technologies that will not experience any additional improvements in design or manufacturing. As a result, we estimate the learning factor for these technologies to be 1.00 in model year 2020 and continue flat through model year 2050. For other basic engine technologies (e.g., VVL, SGDI, DEAC, etc.), we estimate a relatively steep reduction in costs until model year 2036, when we expect costs to remain stable through model year 2050.

All advanced engine technologies, except TURBO2, follow the same general pattern of a gradual reduction in costs until model year 2036 when they plateau and remain flat through model year 2050. We estimate that the TURBO2 learning curve will slightly increase from model year 2020 through model year 2021, decrease slightly through model year 2025, decrease with a slightly steeper curve until model year 2036, where it follows the trend of flattening out through model year 2050. The initial increase in the TURBO2 curve is due to it being a newer technology with low production volumes and an inefficient manufacturing process, which will cause a slight increase in cost. We expect the cost to decrease as production volumes increase, manufacturing processes are improved, and economies of scale are achieved. The rates of the cost decreases are reflected in the shape of the curve from model year 2025 through model year 2050.

In contrast, we consider the AT5 and AT6 transmissions to be mature technologies that will not experience any additional improvements in design or manufacturing. As a result, we estimate the learning factor for these technologies to be 1.00 and 0.99, respectively, in model year 2020 and continue flat through model year 2050. The remaining basic technologies (i.e., AT8, DCT6, and DCT8) are nearly mature; therefore, they experience a gradual reduction in costs from model year 2020 through model year 2031, when they remain constant through model year 2050. Similarly, the learning curves for the remaining TRANS decreases from model year 2020 through model year 2036 and then remains flat through to model year 2050.

We estimate that the learning curves for all the road load technologies – with the exception of MR5 – decrease from model year 2020 through model year 2036 and then remain flat through model year 2050. The learning curve for MR5 follows a different curvature that gradually decreases from model year 2020 through model year 2030, decreases sharper from model year 2031 through model year 2035, and then continues to decrease from model year 2036 through model year 2050 at a shallower rate.

Additionally, the CAFE Model applies AC leakage, AC efficiency, and off-cycle technologies and accounts for their associated costs independent of the technology pathways. As a result, we group their learning curves together to maintain consistency. AC leakage and AC efficiency technologies have the same time-based learning curve, which we consider to be on the flat portion of the curve. Similarly, off-cycle technology also has a time-based learning curve that we consider to be on the flat portion of the curve. Further discussion on AC leakage, AC efficiency, and off-cycle technologies is detailed in Chapter 3.7.

Table 2-28 and Table 2-29 show the learning curve schedule for CAFE Model Non-Electrification Technologies for model years 2020 through 2035 and model years 2036 through 2050, respectively.

Table 2-28: Learning Curve Schedule for CAFE Model Non-Electrification Technologies, MYs 2020-2035

Technology	Model Year															
	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
SOHC, DOHC	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
VVL	0.9318	0.9256	0.9197	0.9142	0.9089	0.9039	0.8990	0.8944	0.8901	0.8859	0.8819	0.8782	0.8782	0.8782	0.8782	0.8782
SGDI	0.9316	0.9254	0.9196	0.9140	0.9088	0.9037	0.8989	0.8943	0.8899	0.8857	0.8818	0.8780	0.8780	0.8780	0.8780	0.8780
DEAC	0.9267	0.9205	0.9147	0.9092	0.9040	0.8989	0.8941	0.8896	0.8852	0.8811	0.8771	0.8734	0.8734	0.8734	0.8734	0.8734
TURBO0	0.7803	0.7709	0.7628	0.7557	0.7500	0.7455	0.7412	0.7370	0.7331	0.7296	0.7264	0.7233	0.7233	0.7233	0.7233	0.7233
TURBOE	0.9554	0.9361	0.9164	0.8985	0.8814	0.8648	0.8494	0.8368	0.8251	0.8148	0.8057	0.7976	0.7976	0.7976	0.7976	0.7976
TURBOD	0.9267	0.9205	0.9147	0.9092	0.9040	0.8989	0.8941	0.8896	0.8852	0.8811	0.8771	0.8734	0.8734	0.8734	0.8734	0.8734
TURBO1	0.9318	0.9256	0.9197	0.9142	0.9089	0.9039	0.8990	0.8944	0.8901	0.8859	0.8819	0.8782	0.8782	0.8782	0.8782	0.8782
TURBO2	1.5985	1.5389	1.4727	1.4114	1.3487	1.2844	1.2248	1.1794	1.1368	1.0996	1.0676	1.0396	1.0396	1.0396	1.0396	1.0396
ADEACD, ADEACS	1.0965	1.0672	1.0427	1.0213	1.0038	0.9886	0.9754	0.9637	0.9529	0.9430	0.9339	0.9255	0.9255	0.9255	0.9255	0.9255
HCR	0.3505	0.3165	0.2901	0.2692	0.2524	0.2387	0.2271	0.2176	0.2096	0.2029	0.1971	0.1920	0.1920	0.1920	0.1920	0.1920
HCRE	0.9554	0.9361	0.9164	0.8985	0.8814	0.8648	0.8494	0.8368	0.8251	0.8148	0.8057	0.7976	0.7976	0.7976	0.7976	0.7976
HCRD	0.9267	0.9205	0.9147	0.9092	0.9040	0.8989	0.8941	0.8896	0.8852	0.8811	0.8771	0.8734	0.8734	0.8734	0.8734	0.8734
VCR	1.1091	1.0795	1.0547	1.0331	1.0154	1.0000	0.9866	0.9748	0.9639	0.9539	0.9447	0.9361	0.9361	0.9361	0.9361	0.9361
VTG	0.9554	0.9361	0.9164	0.8985	0.8814	0.8648	0.8494	0.8368	0.8251	0.8148	0.8057	0.7976	0.7976	0.7976	0.7976	0.7976

VTGE	0.8748	0.8250	0.7821	0.7461	0.7171	0.6889	0.6613	0.6406	0.6144	0.5950	0.5762	0.5640	0.5463	0.5463	0.5463	0.5463
TURBOAD	1.0965	1.0672	1.0427	1.0213	1.0038	0.9886	0.9754	0.9637	0.9529	0.9430	0.9339	0.9255	0.9255	0.9255	0.9255	0.9255
ADSL	0.8503	0.8304	0.8205	0.8106	0.8007	0.8008	0.7968	0.7928	0.7889	0.7849	0.7830	0.7811	0.7791	0.7791	0.7791	0.7791
DSLI	0.8700	0.8500	0.8400	0.8300	0.8200	0.8200	0.8159	0.8118	0.8078	0.8037	0.8017	0.7997	0.7977	0.7977	0.7977	0.7977
CNG	1.0211	1.0105	1.0105	0.9999	0.9999	0.9892	0.9892	0.9786	0.9786	0.9786	0.9680	0.9680	0.9680	0.9680	0.9680	0.9680
AT5	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
AT6	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900
AT7L2	0.8024	0.7776	0.7575	0.7424	0.7300	0.7193	0.7104	0.7040	0.6982	0.6929	0.6882	0.6837	0.6837	0.6837	0.6837	0.6837
AT8	0.9887	0.9883	0.9880	0.9876	0.9873	0.9871	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868
AT8L2	0.7378	0.7050	0.6783	0.6584	0.6420	0.6278	0.6161	0.6076	0.5999	0.5929	0.5865	0.5806	0.5806	0.5806	0.5806	0.5806
AT8L3	0.8025	0.7777	0.7576	0.7425	0.7301	0.7194	0.7106	0.7041	0.6983	0.6931	0.6883	0.6839	0.6839	0.6839	0.6839	0.6839
AT9L2, AT10L2, AT10L3	0.8024	0.7776	0.7575	0.7424	0.7300	0.7193	0.7104	0.7040	0.6982	0.6929	0.6882	0.6837	0.6837	0.6837	0.6837	0.6837
DCT6, DCT8	0.9889	0.9886	0.9883	0.9880	0.9878	0.9875	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873
eCVT	0.9961	0.9945	0.9930	0.9916	0.9903	0.9891	0.9879	0.9868	0.9858	0.9848	0.9839	0.9831	0.9831	0.9831	0.9831	0.9831
CVT, CVTL2	0.8779	0.8696	0.8619	0.8547	0.8480	0.8417	0.8359	0.8303	0.8251	0.8202	0.8156	0.8112	0.8112	0.8112	0.8112	0.8112
CONV	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
ROLL0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

ROLL10	0.8059	0.7882	0.7730	0.7597	0.7478	0.7371	0.7273	0.7185	0.7104	0.7029	0.6961	0.6897	0.6897	0.6880	0.6862	0.6845
ROLL20, ROLL30	0.7154	0.6870	0.6640	0.6452	0.6292	0.6156	0.6038	0.5934	0.5843	0.5762	0.5689	0.5623	0.5623	0.5609	0.5595	0.5581
AERO0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
AERO5, AERO10	0.7947	0.7746	0.7572	0.7422	0.7290	0.7172	0.7067	0.6972	0.6885	0.6807	0.6735	0.6669	0.6669	0.6652	0.6635	0.6619
AERO15	0.4492	0.4378	0.4280	0.4195	0.4120	0.4054	0.3994	0.3941	0.3892	0.3847	0.3807	0.3769	0.3769	0.3760	0.3750	0.3741
AERO20	0.3047	0.2969	0.2903	0.2845	0.2794	0.2749	0.2709	0.2672	0.2639	0.2609	0.2582	0.2556	0.2556	0.2550	0.2544	0.2537
MR0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MR1	1.0883	1.0591	1.0339	1.0121	0.9931	0.9763	0.9613	0.9479	0.9358	0.9248	0.9147	0.9055	0.9055	0.9032	0.9009	0.8987
MR2	0.7722	0.7536	0.7375	0.7234	0.7099	0.6971	0.6856	0.6756	0.6669	0.6589	0.6519	0.6455	0.6455	0.6439	0.6423	0.6407
MR3	0.6618	0.6489	0.6360	0.6240	0.6121	0.6005	0.5902	0.5815	0.5740	0.5674	0.5615	0.5561	0.5561	0.5548	0.5534	0.5520
MR4	0.6936	0.6588	0.6365	0.6194	0.6015	0.5845	0.5677	0.5547	0.5442	0.5355	0.5281	0.5216	0.5216	0.5203	0.5190	0.5177
MR5	1.0000	0.9704	0.9408	0.9112	0.8816	0.8520	0.8276	0.8031	0.7786	0.7541	0.7297	0.6905	0.6513	0.6121	0.5729	0.5337
AC Leakage	1.0000	0.9800	0.9604	0.9412	0.9224	0.9039	0.8858	0.8681	0.8508	0.8337	0.8171	0.8007	0.7847	0.7690	0.7536	0.7386
AC Efficiency	1.0000	0.9800	0.9604	0.9412	0.9224	0.9039	0.8858	0.8681	0.8508	0.8337	0.8171	0.8007	0.7847	0.7690	0.7536	0.7386
Off-Cycle	1.0000	0.9811	0.9686	0.9497	0.9371	0.9245	0.9107	0.8970	0.8835	0.8703	0.8572	0.8444	0.8317	0.8192	0.8069	0.7948

Table 2-29: Learning Curve Schedule for CAFE Model Non-Electrification Technologies, MYs 2036-2050

Technology	Model Year														
	2036	2037	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050

SOHC, DOHC	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
VVL	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782
SGDI	0.8780	0.8780	0.8780	0.8780	0.8780	0.8780	0.8780	0.8780	0.8780	0.8780	0.8780	0.8780	0.8780	0.8780	0.8780
DEAC	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734
TURBO0	0.7233	0.7233	0.7233	0.7233	0.7233	0.7233	0.7233	0.7233	0.7233	0.7233	0.7233	0.7233	0.7233	0.7233	0.7233
TURBOE	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976
TURBOD	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734
TURBO1	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782	0.8782
TURBO2	1.0396	1.0396	1.0396	1.0396	1.0396	1.0396	1.0396	1.0396	1.0396	1.0396	1.0396	1.0396	1.0396	1.0396	1.0396
ADEACD, ADEACS	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255
HCR	0.1920	0.1920	0.1920	0.1920	0.1920	0.1920	0.1920	0.1920	0.1920	0.1920	0.1920	0.1920	0.1920	0.1920	0.1920
HCRE	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976
HCRD	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734	0.8734
VCR	0.9361	0.9361	0.9361	0.9361	0.9361	0.9361	0.9361	0.9361	0.9361	0.9361	0.9361	0.9361	0.9361	0.9361	0.9361
VTG	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976	0.7976
VTGE	0.5463	0.5463	0.5463	0.5463	0.5463	0.5463	0.5463	0.5463	0.5463	0.5463	0.5463	0.5463	0.5463	0.5463	0.5463
TURBOAD	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255	0.9255

ADSL	0.7791	0.7791	0.7791	0.7791	0.7791	0.7791	0.7791	0.7791	0.7791	0.7791	0.7791	0.7791	0.7791	0.7791	0.7791
DSLI	0.7977	0.7977	0.7977	0.7977	0.7977	0.7977	0.7977	0.7977	0.7977	0.7977	0.7977	0.7977	0.7977	0.7977	0.7977
CNG	0.9680	0.9680	0.9680	0.9680	0.9680	0.9680	0.9680	0.9680	0.9680	0.9680	0.9680	0.9680	0.9680	0.9680	0.9680
AT5	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
AT6	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900
AT7L2	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837
AT8	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868	0.9868
AT8L2	0.5806	0.5806	0.5806	0.5806	0.5806	0.5806	0.5806	0.5806	0.5806	0.5806	0.5806	0.5806	0.5806	0.5806	0.5806
AT8L3	0.6839	0.6839	0.6839	0.6839	0.6839	0.6839	0.6839	0.6839	0.6839	0.6839	0.6839	0.6839	0.6839	0.6839	0.6839
AT9L2, AT10L2, AT10L3	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837	0.6837
DCT6, DCT8	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873	0.9873
eCVT	0.9831	0.9831	0.9831	0.9831	0.9831	0.9831	0.9831	0.9831	0.9831	0.9831	0.9831	0.9831	0.9831	0.9831	0.9831
CVT, CVTL2	0.8112	0.8112	0.8112	0.8112	0.8112	0.8112	0.8112	0.8112	0.8112	0.8112	0.8112	0.8112	0.8112	0.8112	0.8112
CONV	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
ROLL0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
ROLL10	0.6828	0.6811	0.6794	0.6777	0.6760	0.6743	0.6726	0.6710	0.6693	0.6676	0.6659	0.6643	0.6626	0.6610	0.6593
ROLL20, ROLL30	0.5567	0.5553	0.5539	0.5525	0.5511	0.5498	0.5484	0.5470	0.5456	0.5443	0.5429	0.5416	0.5402	0.5389	0.5375

AERO0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
AERO5, AERO10	0.6602	0.6586	0.6569	0.6553	0.6537	0.6520	0.6504	0.6488	0.6471	0.6455	0.6439	0.6423	0.6407	0.6391	0.6375
AERO15	0.3732	0.3722	0.3713	0.3704	0.3695	0.3685	0.3676	0.3667	0.3658	0.3649	0.3639	0.3630	0.3621	0.3612	0.3603
AERO20	0.2531	0.2525	0.2518	0.2512	0.2506	0.2499	0.2493	0.2487	0.2481	0.2474	0.2468	0.2462	0.2456	0.2450	0.2444
MR0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MR1	0.8964	0.8942	0.8920	0.8897	0.8875	0.8853	0.8831	0.8809	0.8787	0.8765	0.8743	0.8721	0.8699	0.8677	0.8656
MR2	0.6391	0.6375	0.6359	0.6343	0.6327	0.6311	0.6295	0.6280	0.6264	0.6248	0.6233	0.6217	0.6202	0.6186	0.6171
MR3	0.5506	0.5492	0.5479	0.5465	0.5451	0.5438	0.5424	0.5410	0.5397	0.5383	0.5370	0.5357	0.5343	0.5330	0.5316
MR4	0.5164	0.5151	0.5138	0.5125	0.5112	0.5099	0.5087	0.5074	0.5061	0.5049	0.5036	0.5023	0.5011	0.4998	0.4986
MR5	0.5231	0.5126	0.5024	0.4923	0.4825	0.4728	0.4634	0.4541	0.4450	0.4361	0.4274	0.4188	0.4105	0.4022	0.3942
AC Leakage	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238
AC Efficiency	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238	0.7238
Off-Cycle	0.7829	0.7829	0.7829	0.7829	0.7829	0.7829	0.7829	0.7829	0.7829	0.7829	0.7829	0.7829	0.7829	0.7829	0.7829

2.5. Simulating Existing Incentives, Government Programs, and Non-regulatory ZEV Deployment

The compliance analysis also requires inputs and assumptions specifying, when applicable, incentives or government programs that either reduce the cost of specific vehicle technologies or increase the penetration of specific vehicle technologies., and additional manufacturer non-regulatory deployment of electric vehicles. The following subchapters discuss inputs and assumptions relating to how we model ZEV programs in Section 177 States, non-regulatory deployment of electric vehicles, and IRA tax credits.

2.5.1. Simulating the Zero Emissions Vehicle (ZEV) Programs in Section 177 States – LD CAFE and HDPUV FE – and Additional Non-Regulatory ZEV Deployment

CARB has developed various programs to control emissions of criteria pollutants and greenhouse gas emissions from vehicles sold in California. The ZEV program for light-duty vehicles began in 1990, within the low-emission vehicle (LEV) regulation,[205] and was adopted by a variety of other states; these states are sometimes referred to as Section 177 states, in reference to Section 177 of the CAA.[206] This program is now referred to as ACC I for model year 2018 through 2025. For model years 2026 and beyond, the regulatory program is ACC II, which has not been granted a waiver of Clean Air Act preemption by EPA and is therefore not currently enforceable. CARB established a ZEV program for heavy duty vehicles in 2021, called ACT.[207]

It is important to note that not all Section 177 states have adopted the ACC I, ACC II, or ACT program components.[208] Various states have also chosen to opt in to the ACC I or ACC II program across different model years. The discussion in the following chapters will refer to states that have adopted any component of the light-duty ZEV programs as “ACC I/ACC II states”, and the states that have adopted the ACT program will be called “ACT states.” In another layer of complexity, many states signed a memorandum of understanding (MOU) in 2020 to indicate their intent to work collaboratively towards a goal of turning 100% of medium-duty and heavy-duty vehicles into ZEVs in the future.[209] For the purposes of CAFE analysis, we include only those states that have adopted the ACT in our modeling as “ACT states,” and do not include states that have signed the MOU without formally adopting an ACT program. When the term “ZEV programs” is used hereafter, it refers to both the ACC I/ACC II and ACT programs.

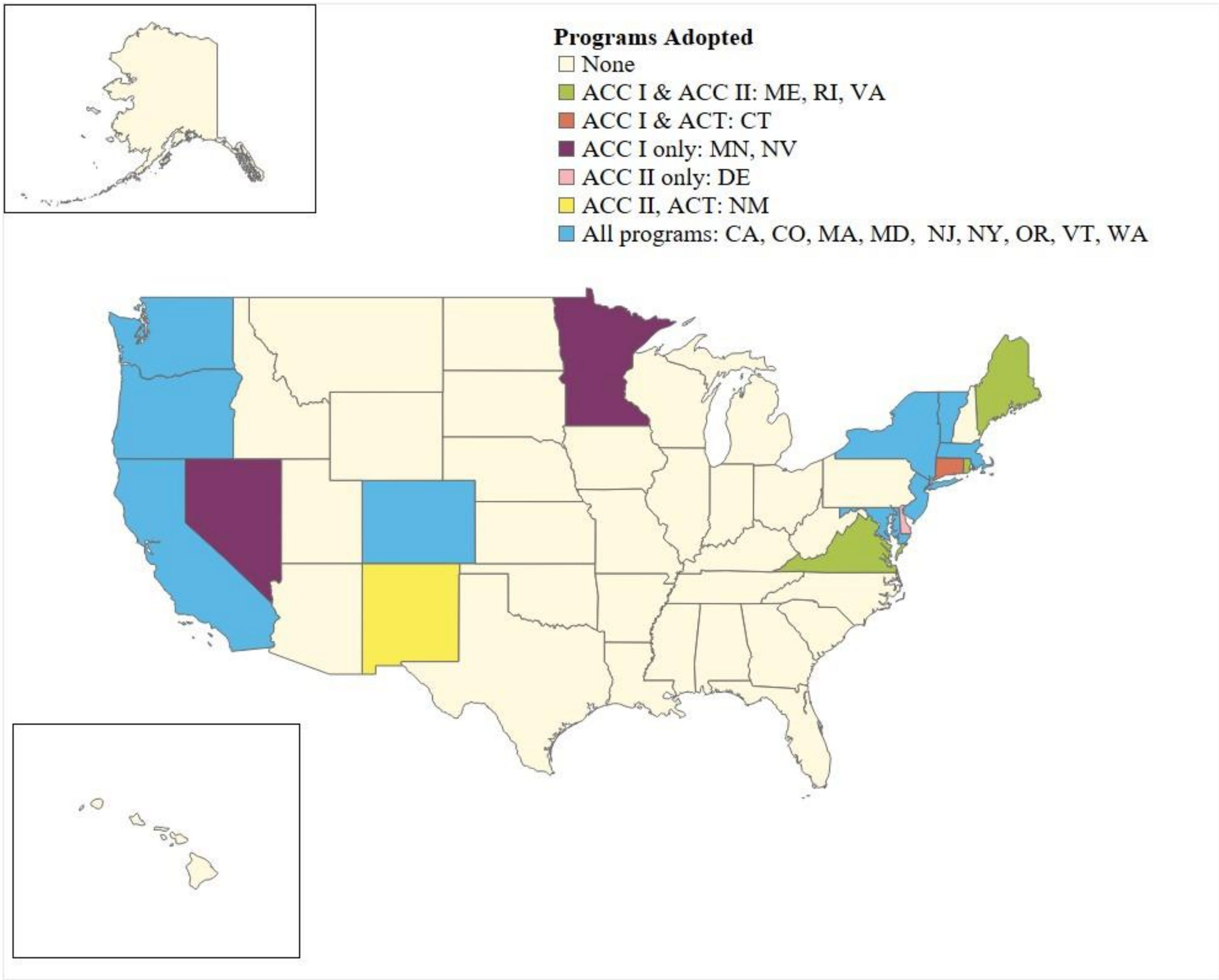
NHTSA incorporates the ACC I and ACT programs into the reference baseline as requirements that are legally binding on manufacturers and which therefore NHTSA believes will be complied with and lead to changes in the baseline fleet that are wholly independent of NHTSA’s standards. ACC II has not been granted a waiver and is not currently legally binding. However, as discussed in the preamble, manufacturers have committed to voluntarily deploying electric vehicles at levels consistent with or beyond those that would be required by ACC II, were it to be granted a waiver. As such, NHTSA also incorporates levels of electric vehicle deployment that would be consistent with ACC II as a conservative proxy for these commitments which will also alter the fleet wholly independently of NHTSA’s standards.

Figure 2-11 shows the states that have adopted or are in the process of adopting one or more of the CARB Zero-Emission Vehicle programs at the time of analysis. ACC I states in our modeling (that have joined in at least one model year) are: California, Colorado, Connecticut, Maine, Maryland, Massachusetts, Minnesota, Nevada, New Jersey, New York, Oregon, Rhode Island, Vermont, Virginia, and Washington. ACC II states are: California, Colorado, Delaware, Maine, Maryland, Massachusetts, New Jersey, New Mexico, New York, Oregon, Rhode Island, Vermont, Virginia, and Washington. We model California, Colorado, Connecticut,

[205] California Air Resource Board (CARB). 2023. Zero-Emission Vehicle Program. Available at: https://ww2.arb.ca.gov/our-work/programs/zero-emission-vehicle-program/about. (Accessed: Feb. 8, 2024).
[206] Section 177 of the CAA allows other states to adopt California’s air quality standards.
[207] California Air Resource Board (CARB). 2023. Final Regulation Order: Advanced Clean Trucks Regulation. Available at: https://ww2.arb.ca.gov/sites/default/files/2023-06/ACT-1963.pdf. (Accessed: Mar. 24, 2024).
[208] At the time of analysis, Pennsylvania is the state that has adopted the LEV standards, but not the ZEV (now ACC II) portion. See Pennsylvania Department of Environmental Protection. Clean Vehicle Program. Available at: https://www.dep.pa.gov/Business/Air/BAQ/Automobiles/Pages/CleanVehicleProgram.aspx. (Accessed: Dec. 18, 2023).
[209] Northeast States for Coordinated Air Use Management (NESCAUM). Multi-State Medium and Heavy-Duty Zero Emission Vehicle Memorandum of Understanding. July 13, 2020. Available at: https://www.nescaum.org/documents/mhdv-zev-mou-20220329.pdf/. (Accessed: Dec. 18, 2023).

Maryland, Massachusetts, New Jersey, New Mexico, New York, Oregon, Vermont, and Washington as being part of the ACT program.[210]

Figure 2-11: ACC I, ACC II, and ACT States



To account for ACC I and ACT and additional voluntary deployment of ZEVs consistent with ACC II, and particularly as other states have recently adopted California's ZEV standards, NHTSA has included the main provisions of the ACC I/ACC II and ACT programs in the CAFE Model's analysis. As explained in further detail in the following chapters, incorporating these programs into the model includes converting vehicles that have been identified as potential ZEV candidates into BEVs so that a manufacturer's fleet is consistent with the calculated ZEV credit requirements.[211] The CAFE Model aligns manufacturers fleets consistent with ACC I/ACC II and ACT first in the reference baseline, then solves for the technology compliance pathway used to be consistent with increasing ZEV targets. The two programs have different requirements per model year, so they are modeled separately in the CAFE analysis. Chapter 2.5.1 describes the two programs, Chapter

[210] See the rulemaking docket NHTSA-2023-0022.for a complete list of pdf citations.
[211] NHTSA made the decision to focus on BEVs for ZEV compliance based on several factors; first, because CARB only allows partial compliance with PHEVs, second, because NHTSA had conversations with manufacturers that indicated some would not be manufacturing PHEVs, and third, because including PHEVs in the ZEV modeling would have introduced unnecessary complication. Further discussion of NHTSA's decision to focus on BEVs for ZEV compliance rather than PHEVs is located in the preamble.

2.5.1.2 discusses the calculation of ZEV credit targets, and Chapter 2.5.1.3 describes how the model treats ZEV candidates in the analysis fleet.

2.5.1.1. Overview of the ZEV Programs

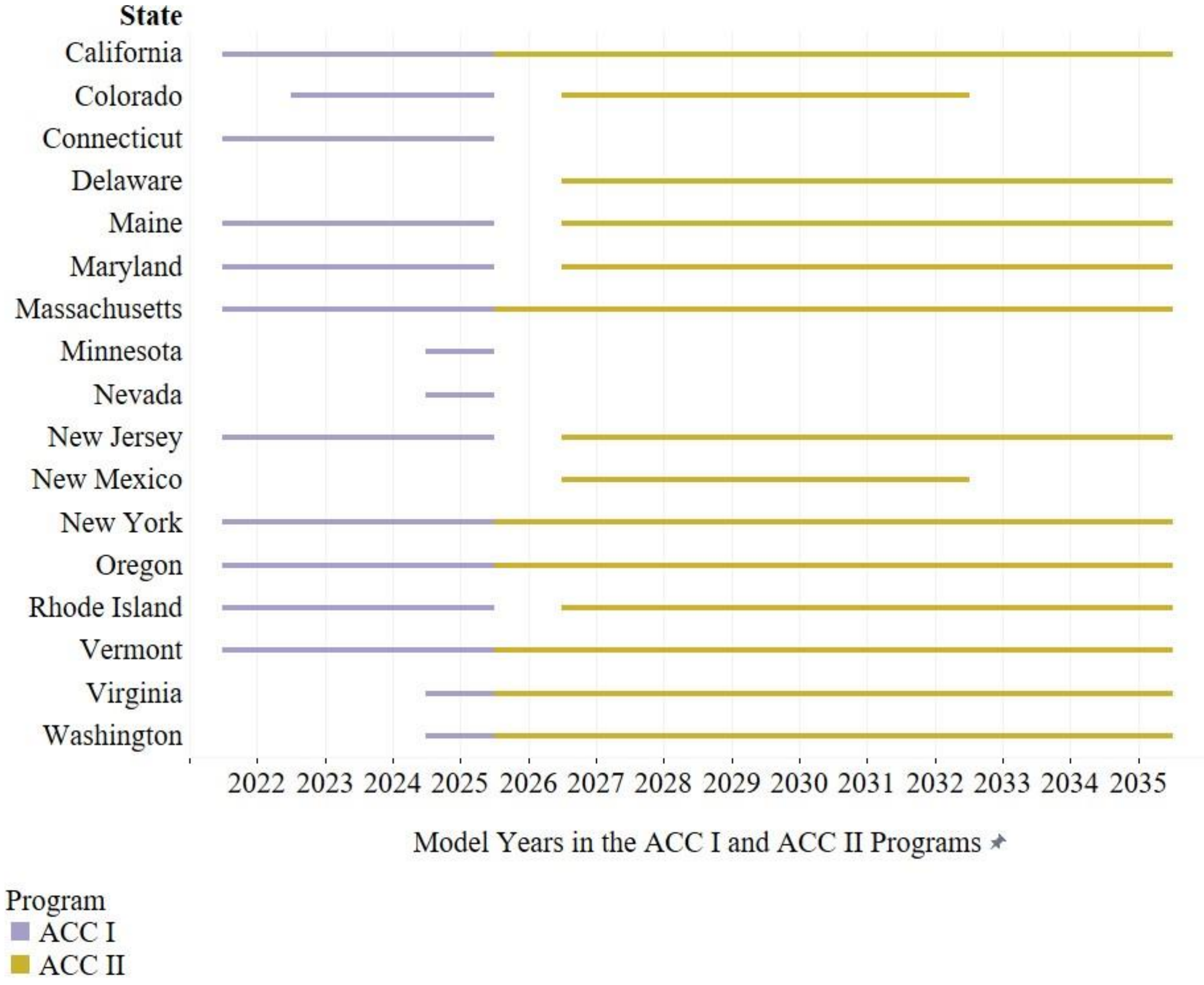
Since the CAFE Model's base year for this analysis is model year 2022, we include both ACC I (light-duty ZEV requirements through 2025) and ACC II (ZEV requirements from 2026-2035) in our modeling. In this document, we refer to the collective CARB ZEV requirements for light-duty vehicles as the "ACC Program." "ZEVs" can refer to either BEVs, FCEVs, or PHEVs, as each can earn differing amounts of credits under CARB's programs. "Full ZEVs" refers to BEVs and FCEVs in the context of this subchapter,[212] as a PHEV generally receives a smaller number of credits than other ZEVs since its powertrain still incorporates use of an ICE.

2.5.1.1.1. ACC I and ACC II Program

On November 30, 2022, CARB finalized the ACC II standards, which include a ZEV component. While ACC II is not currently enforceable while CARB's waiver request for the program is under consideration by EPA (in contrast to ACC I and ACT, which have already received waiver approvals), manufacturers have indicated that they intend to deploy additional electric vehicles consistent with (or beyond) what ACC II would require for compliance if a waiver were to be granted. The ZEV standards that were in place before the ACC II standards, that go through model year 2025, are part of the ACC I program. At the time of analysis, seventeen states in addition to California either formally signed on to either the ACC I or ACC II standards or were in the process of adopting them.[213] Out of these states, many are adopting the ACC I and ACC II standards in different model years, or they adopt one program but not the other. Figure 2-12 shows the model years in which the states are committed to or in the process of adopting the programs (at the time of NHTSA's analysis).

[212] Although FCEVs can earn the same number of credits as BEVs, NHTSA chooses to focus on BEVs when adding ZEV candidates to the fleet, since FCEVs are generally less cost-effective than BEVs and most manufacturers have not been producing them at high volumes.
[213] California, Colorado, Connecticut, Delaware, Maine, Maryland, Massachusetts, Minnesota, Nevada, New York, New Jersey, New Mexico, Oregon, Rhode Island, Vermont, Virginia, and Washington..See ZEV State References in docket NHTSA-2023-0022.

Figure 2-12: States' ACC I and ACC II Model Year Commitments[214]

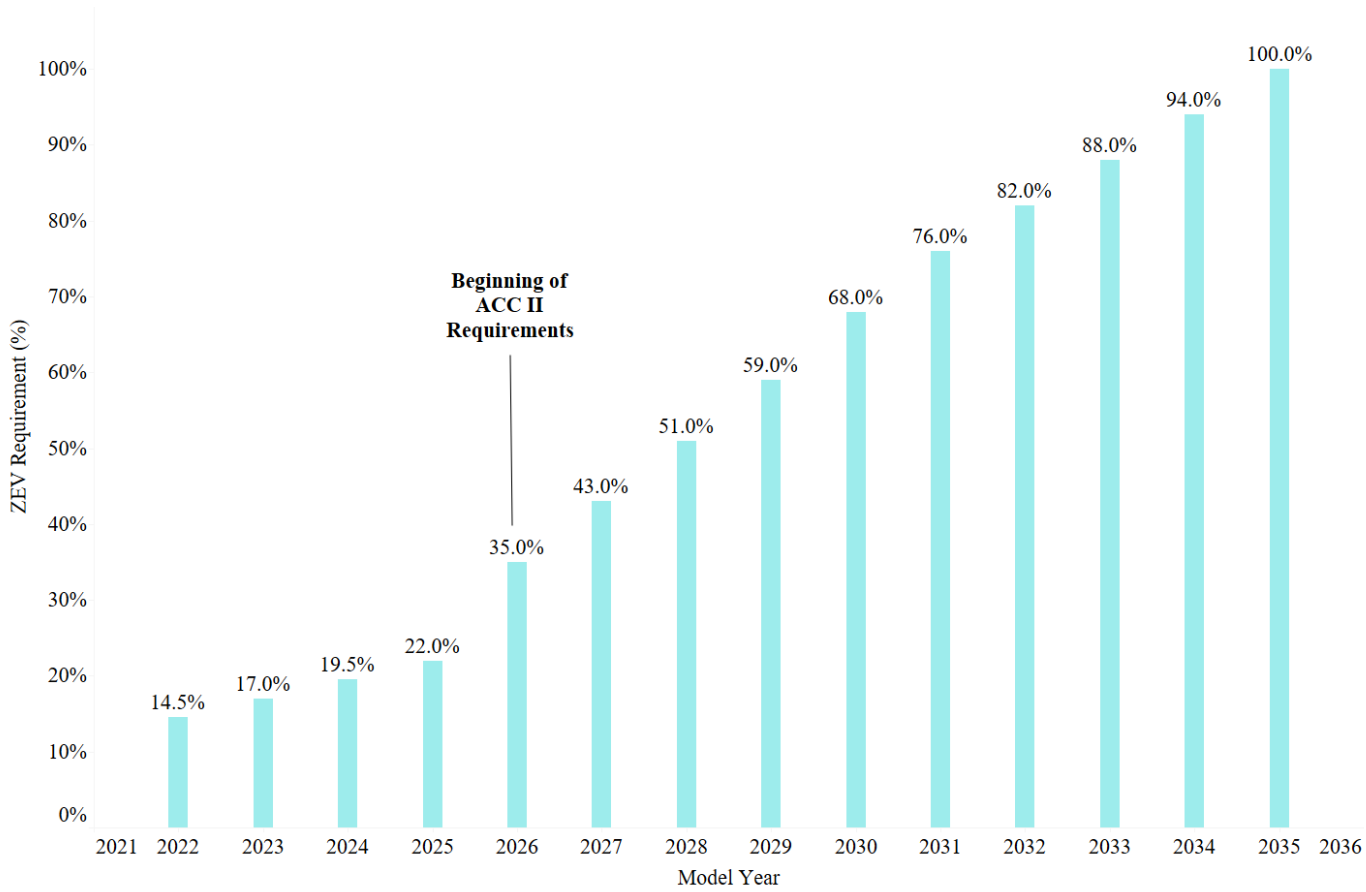


California requires that all manufacturers that sell light-duty vehicles within the state meet the ZEV requirements, which specify that a certain percentage of vehicles sold be ZEVs. The percentage requirement increases in each model year. CARB also specifies a maximum percentage of ZEV credits that can be met through PHEV presence in the fleet, as shown in Figure 2-13. From 2026-2035, manufacturers cannot earn more than 20% of their ZEV credits through PHEV sales. In model years prior to 2026, the PHEV percentage cap does not apply to lower-volume manufacturers. The steeper increase in requirements from 2025 to 2026 reflects the change from the ACC I Program to the ACC II Program. Note that prior to 2026, a ZEV could earn up to 4 credits depending on range, while ZEVs sold in 2026 and later can only earn up to 1 credit per vehicle. By 2035, the ACC II Program aims to have all new light-duty vehicles sold in the ACC II states be ZEVs (these could include a mix of BEVs, FCEVs, and PHEVs, up to the 20% PHEV credit limit).[215]

The ACC II Program also includes compliance options for providing reduced-price ZEVs to community mobility programs and for selling used ZEVs. However, we do not include these in our modeling as they are focused on a more local level than we could reasonably represent in the CAFE Model. The data for this part of the program is not currently available from real world application.

[214] See ZEV State References in NHTSA docket NHTSA-2023-0022.
[215] Note that PHEVs can only account for 20% of a manufacturer's ZEV compliance.

Figure 2-13: ZEV Credit Percentage Requirements Schedule[216]



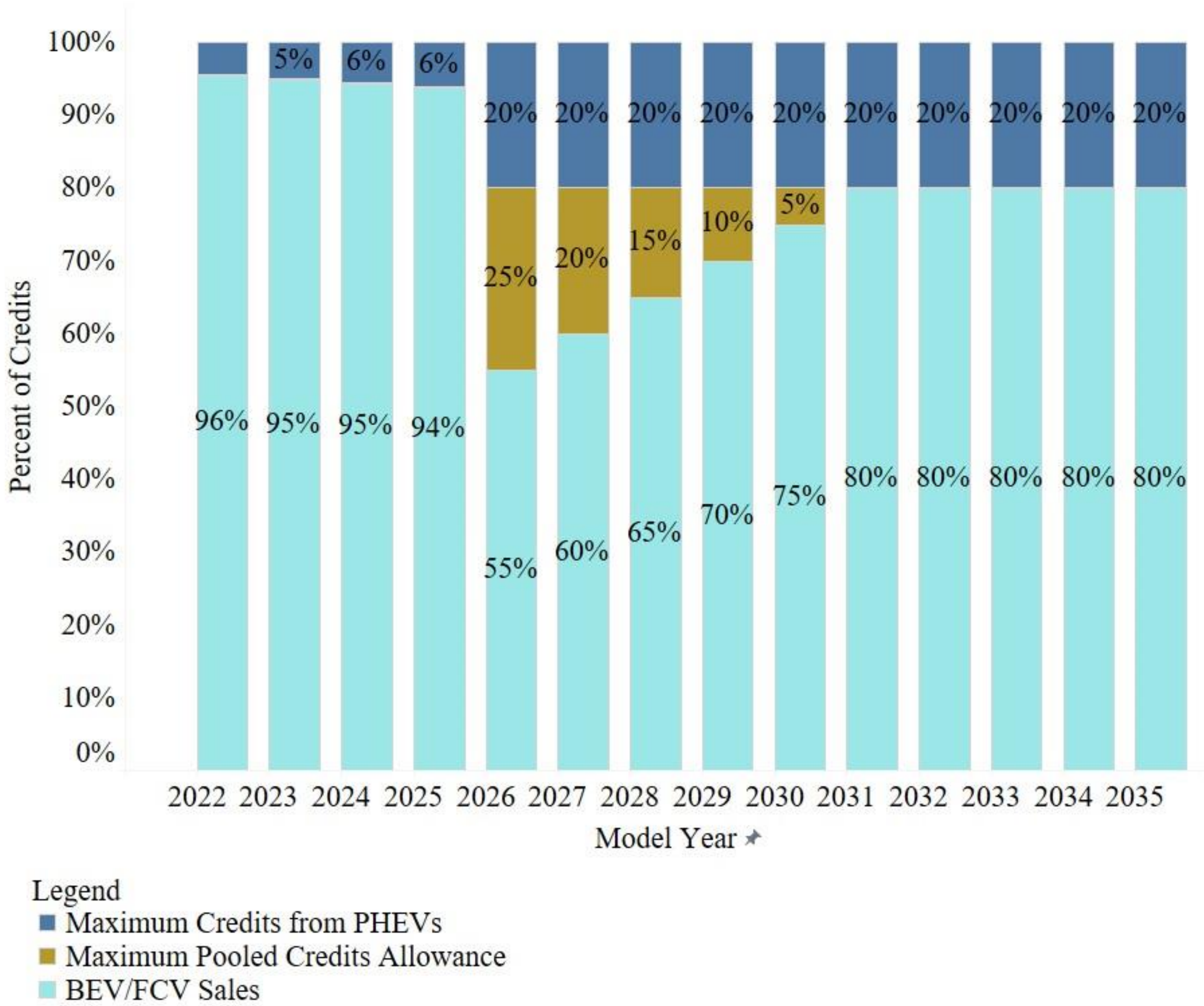
Total ACC II credits required are the product of manufacturers' ACC II state sales volumes and the ZEV percentage requirements. For example, a manufacturer selling 100,000 vehicles in California and 10,000 vehicles in Connecticut in model year 2028 must ensure that 51,000 of the California vehicles and 5,100 of the Connecticut vehicles are ZEVs.

CARB allows for some banking of ZEV credits and credit pooling.[217] Under the ACC II program, manufacturers may use up to a certain fixed percentage of pooled credits between model years 2026-2030 to offset a shortfall. In our modeling, we account for this allowance by reducing the ZEV requirement assumed to be met through vehicle sales by this pooled credits percentage allowance.

Figure 2-14 shows the maximum percentages of pooled credits and credits from PHEVs allowed by CARB relative to the full credit percentage requirement.

[216] California Air Resources Board (CARB). 2023. Advanced Clean Cars II Regulations: All New Passenger Vehicles Sold in California to be Zero Emissions by 2035. Available at: https://ww2.arb.ca.gov/our-work/programs/advanced-clean-cars-program/advanced-clean-cars-ii. (Accessed: Apr. 4, 2024).
[217] California Air Resources Board (CARB). 2019. Final Regulation Order: Section 1962.4, Title 13, California Code of Regulations. Available at: https://ww2.arb.ca.gov/sites/default/files/barcu/regact/2022/accii/acciifro1962.2.pdf. (Accessed: Apr. 4, 2024).

Figure 2-14: Maximum Credits Allowed from PHEV Sales and Pooled Credits



Total credits achieved are calculated by multiplying the credit value each ZEV receives by the vehicle's volume. Under the ACC II program, from model year 2026 onwards, each full ZEV earns one credit value per vehicle, while partial ZEVs (PHEVs) earn credits based on their AER, according to the formula in Equation 2-6. PHEVs may earn up to one credit each; the PHEV50s in our analysis fleet all have a high enough range value to earn the maximum 0.85 range credit value according to the range formula, plus an additional 0.15 partial credit value for the US06 AER exceeding 10 miles.[218] Note that this formula, Equation 2-6 below, is relevant only for PHEVs with a US06 AER value of 40 miles or greater, since PHEVs with a lower AER do not count at all towards ZEV compliance under the ACC II program.

Equation 2-6: Partial ZEV (PHEV) Credit Formula Under ACC II

$$\textit{Partial ZEV (PHEV) credit value} = \frac{\textit{Certification Range Value}}{100} + 0.20$$

Prior to model year 2026, under the ACC I program, BEVs earn varying amounts of credits depending on their range, with a cap of 4 credits per vehicle, as shown below in Equation 2-7

[218] California Air Resources Board (CARB).2019. Final Regulation Order: Section 1962.4, Title 13, California Code of Regulations. Available at https://ww2.arb.ca.gov/sites/default/files/barcu/regact/2022/accii/2acciifro1962.4.pdf. (Accessed: Apr. 4, 2024).

Equation 2-7: ZEV Credit Calculation per BEV Under ACC I

$$ZEV\ credit\ value = \frac{Range\ Value}{100} + 0.50$$

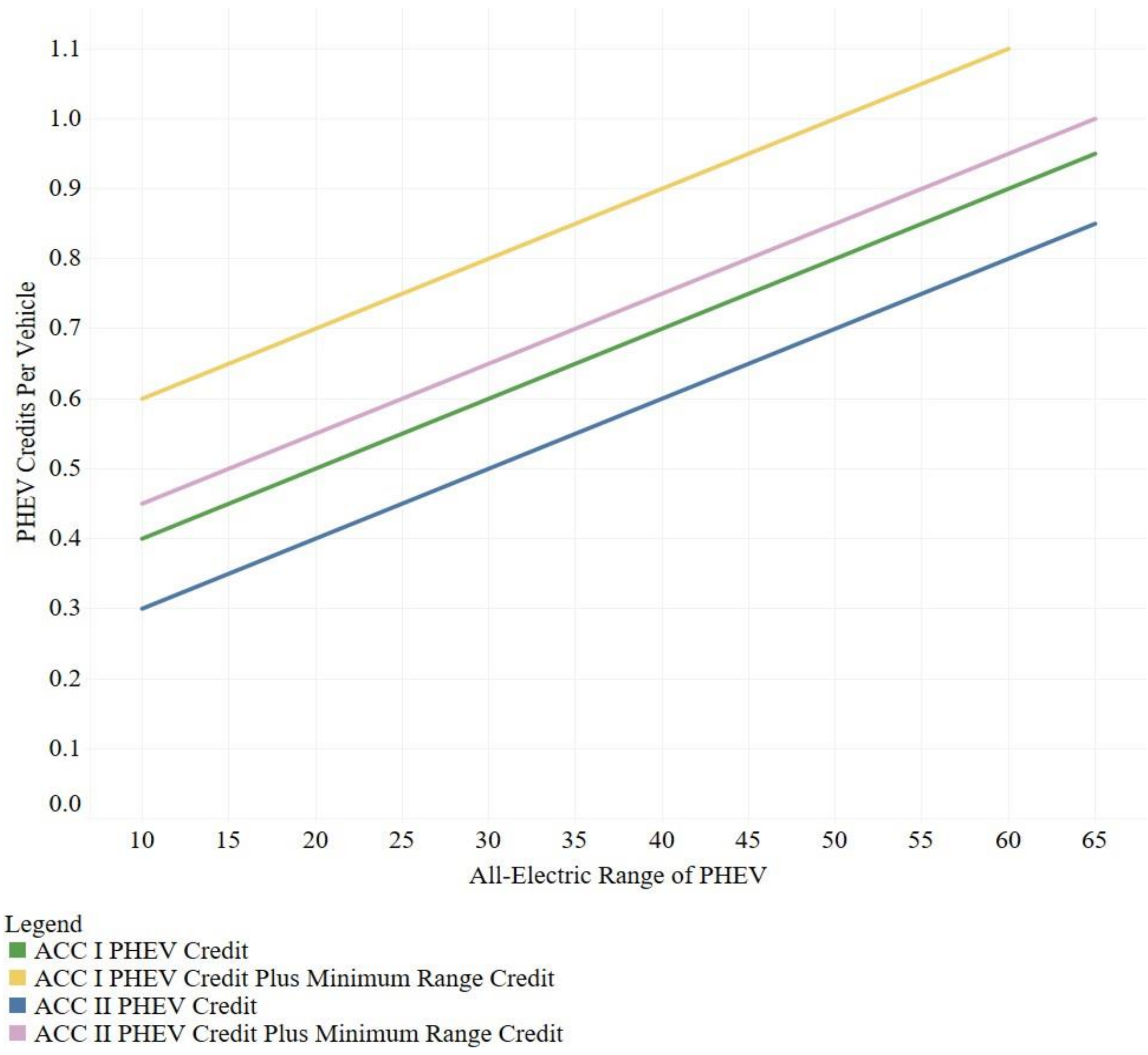
The ACC I program's PHEV credit allowances also vary by AER of the vehicle. The formula for calculating PHEV credits per vehicle is shown below in Equation 2-8. PHEVs with an AER of 10 miles or greater also earn an additional 0.2 credit allowance on top of the credits calculated from the range formula.[219]

Equation 2-8: Partial ZEV (PHEV) Credit Formula Under ACC I

$$Partial\ ZEV\ (PHEV) credit\ value = (0.01 * \ all\text{-}electric\ range\ ) + 0.30$$

Figure 2-15 illustrates the PHEV credit formulas under each program, showing the credits earned per vehicle at each PHEV AER, with and without the minimum range credits.

Figure 2-15: PHEV ACC I/ACC II Credit Values Based on All-Electric Range



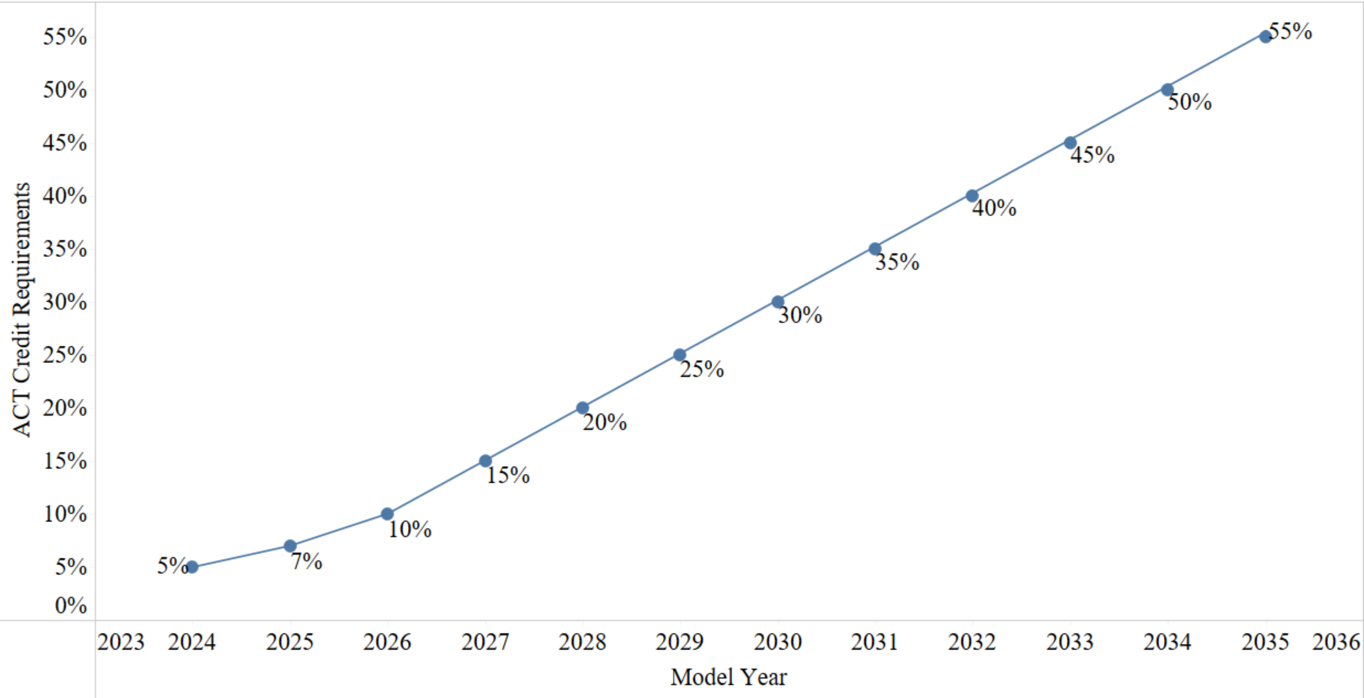
[219] California Air Resources Board (CARB).2019. Final Regulation Order: Section 1962.4, Title 13, California Code of Regulations. Available at: https://ww2.arb.ca.gov/sites/default/files/barcu/regact/2022/accii/acciifro1962.2.pdf. (Accessed: Apr. 4, 2024).

2.5.1.1.2. ACT Program

CARB established zero emissions vehicle standards for trucks in Classes 2b through 8 in 2021, focusing on model years 2024-2035. For Class 2b and 3 vehicles (which are the weight classes that correspond to the HDPUVs considered in this analysis), the 2035 goal aims for 55 percent of vehicles sold in California and ACT states to be ZEVs or qualifying near zero-emissions vehicles (NZEVs).[220] See Figure 2-16 for the year-by-year percentage requirements.

Eleven states, including California, have formally adopted the standards at the time of analysis.[221]

Figure 2-16: ZEV Sales Percentage Requirements for Class 2b and 3 Trucks in MY 2024-2035



Credit targets (referred to as deficits in this program) are calculated by multiplying sales by percentage requirement and weight class multiplier. For the 2b/3 class, the weight modifier is 0.8. Each heavy-duty pickup or van full ZEV in the 2b/3 class earns 0.8 credits and each NZEV (called PHEVs in the CAFE Model) earns 0.75 credits.[222]

2.5.1.2. Calculation of ZEV Credit Targets per Manufacturer

For the purposes of simulating the ZEV programs, we calculated approximate ZEV credit targets as a first step in adding ZEV compliance to the reference baseline. We built these credit targets based on estimation of national sales volumes by manufacturer, analysis of manufacturers' market share in ACC II and ACT states, and application of CARB's credit requirement formulas.

2.5.1.2.1. Characterizing the Market

The CAFE Model is designed to present outcomes at a national scale, so the analysis of the ZEV programs considers the states as a group as opposed to estimating each state's ZEV credit requirements individually.

[220] California Air Resources Board (CARB). 2023. Final Regulation Order: Advanced Clean Trucks Regulation. Available at: https://ww2.arb.ca.gov/sites/default/files/barcu/regact/2019/act2019/fro2.pdf. (Accessed: Mar. 24, 2024).
[221] California, Colorado, Connecticut, Maryland, Massachusetts, New Jersey, New Mexico, New York, Oregon, Vermont, and Washington. We include Connecticut as their House passed the legislation instructing their Department of Energy and Environmental Protection to adopt ACT. See ZEV States citations docket folder NHTSA-2023-0022.
[222] California Air Resources Board (CARB).2023. Final Regulation Order: Advanced Clean Trucks Regulation. Available at: https://www.cga.ct.gov/2022/fc/pdf/2022HB-05039-R000465-FC.pdf. (Accessed: Mar. 24, 2024).

To capture the appropriate volumes subject to ACC II and the ACT requirements, we calculate each manufacturer's total market share in ACC II or ACT states respectively. Due to several states having different ZEV program start and end years,[223] as discussed in the previous section, we include different market shares per manufacturer in each model year.

We use Polk's National Vehicle Population Profile (NVPP) from January 2022 to calculate these percentages.[224] These data include vehicle characteristics such as powertrain, fuel type, manufacturer, nameplate, and trim level, and state in which vehicles were sold. At the time of the data snapshot, model year 2021 data from the NVPP contained the most current estimate of new vehicle market shares for most manufacturers, and best represented the registered vehicle population on January 1, 2022. We assume that new registrations data best approximates new vehicle sales, given the data options. Any variation between the model year shares by manufacturer is due only to the fluctuations in the number of states that are part of the ACC I or ACC II group in that model year, since the NVPP data year remains constant.

2.5.1.2.1.1. Sales in ACC II States

Using model year 2021 NVPP data, the ACC II State group at its largest makes up approximately 38% of the total light-duty sales in the U.S. Figure 2-17 gives the context of how light-duty sales are distributed across states in the U.S., with California, Texas, and Florida having the largest sales percentages.

[223] For example, New Mexico adopts the ACC II requirements beginning in model year 2027 and plans to keep them in place only through 2032, when the standards require 82% ZEVs https://www.env.nm.gov/transportation/.
[224] National Vehicle Population Profile (NVPP). 2022. Includes content supplied by IHS Markit; Copyright R.L. Polk & Co., 2022. All rights reserved. Available at: https://repository.duke.edu/catalog/caad9781-5438-4d65-b908-bf7d97a80b3a. (Accessed: Apr. 4, 2024).

Figure 2-17: Percent of Annual U.S. Light-Duty Vehicle Sales Sold in Each State (MY 2021)

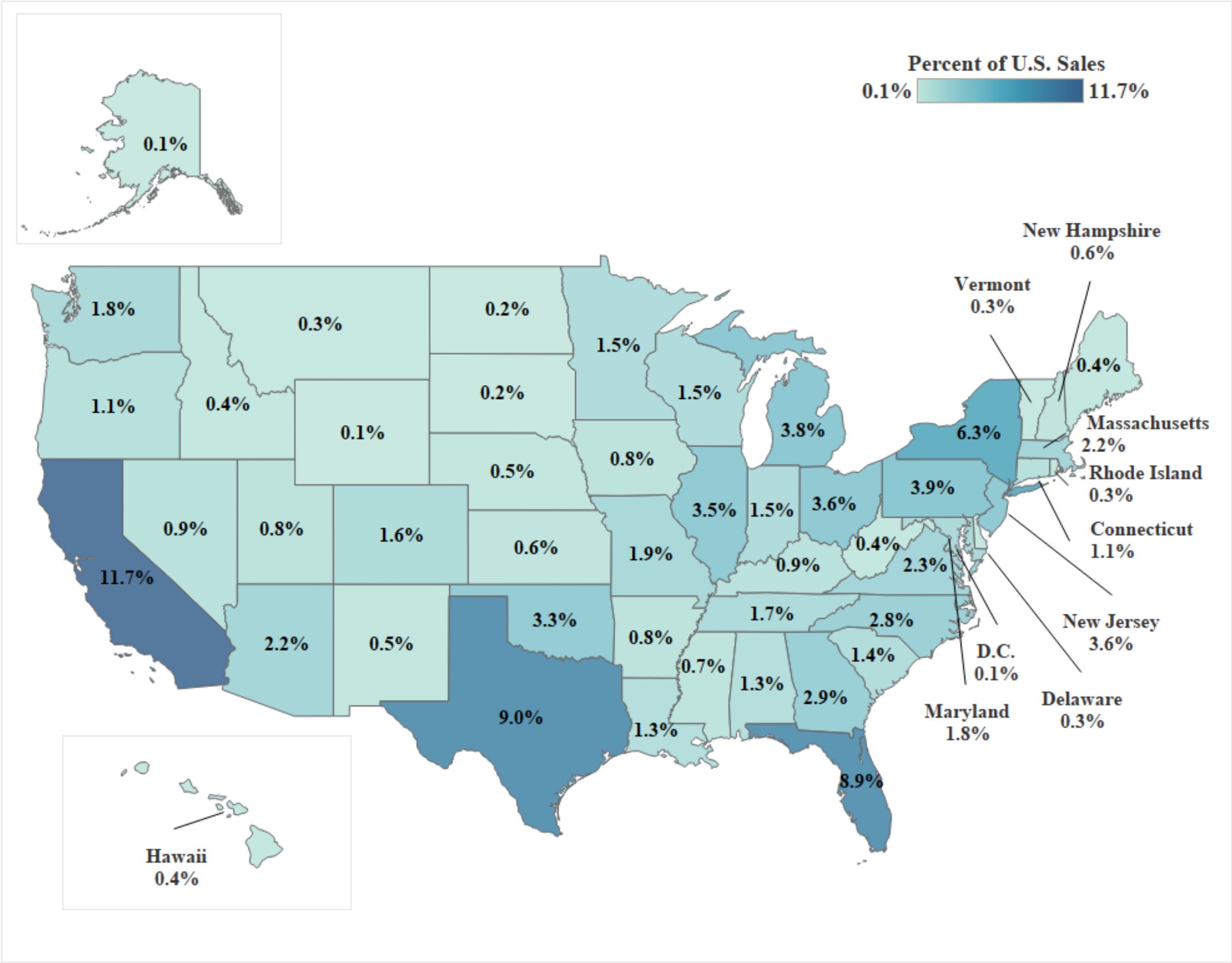


Figure 2-18 shows the percentages of each manufacturer's national sales in the ACC I/ACC II groups by model year, which range from approximately 16% to 62%, depending on the number of states participating in that year and the geographic sales share of the manufacturer.[225] Again, these percentages only vary across model years according to changing numbers of states adopting the standards in that year, since the underlying vehicle sales estimates from the NVPP remain the same. The manufacturers listed are ordered in terms of largest U.S. sales volumes to give additional context.

[225] As the NVPP contained a limited number of data points for Karma, Lucid, and Rivian (which are 100% ZEV manufacturers), we made the simplifying assumption that they would sell 50% of their vehicles in ACC II states, a percent between the value of the other all-electric vehicle company in the data, Tesla (60%), and the manufacturers' average (40%).

Figure 2-18: Manufacturer Sales Shares in ACC I/ACC II States by Model Year[226]

	Year											
	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
Toyota	31.4%	33.2%	33.2%	40.7%	29.8%	38.1%	38.1%	38.1%	38.1%	38.1%	38.1%	35.8%
GM	19.3%	20.5%	20.5%	25.6%	16.8%	23.2%	23.2%	23.2%	23.2%	23.2%	23.2%	21.4%
Honda	35.6%	36.8%	36.8%	43.9%	31.7%	41.5%	41.5%	41.5%	41.5%	41.5%	41.5%	40.0%
FCA (Stellantis)	24.4%	26.1%	26.1%	31.7%	20.5%	28.7%	28.7%	28.7%	28.7%	28.7%	28.7%	26.5%
Ford	20.6%	22.2%	22.2%	28.2%	18.2%	26.0%	26.0%	26.0%	26.0%	26.0%	26.0%	23.8%
Subaru	36.0%	39.4%	39.4%	49.5%	33.2%	45.0%	45.0%	45.0%	45.0%	45.0%	45.0%	41.0%
VWA	34.1%	36.0%	36.0%	42.3%	29.2%	39.2%	39.2%	39.2%	39.2%	39.2%	39.2%	37.0%
Nissan	23.4%	24.6%	24.6%	29.4%	19.2%	27.2%	27.2%	27.2%	27.2%	27.2%	27.2%	25.3%
Tesla	51.4%	53.4%	53.4%	61.5%	50.0%	58.6%	58.6%	58.6%	58.6%	58.6%	58.6%	56.5%
Hyundai Kia-H	27.8%	29.2%	29.2%	36.0%	22.8%	33.0%	33.0%	33.0%	33.0%	33.0%	33.0%	31.2%
Hyundai Kia-K	23.9%	25.3%	25.3%	31.6%	22.1%	29.6%	29.6%	29.6%	29.6%	29.6%	29.6%	27.7%
BMW	44.1%	45.6%	45.6%	50.8%	36.5%	47.9%	47.9%	47.9%	47.9%	47.9%	47.9%	46.2%
Mazda	35.8%	37.5%	37.5%	45.0%	30.4%	41.3%	41.3%	41.3%	41.3%	41.3%	41.3%	39.1%
Daimler (Mercedes-Benz)	44.6%	45.8%	45.8%	50.5%	38.4%	48.3%	48.3%	48.3%	48.3%	48.3%	48.3%	46.8%
Volvo	39.7%	41.8%	41.8%	48.5%	31.4%	45.4%	45.4%	45.4%	45.4%	45.4%	45.4%	43.2%
JLR	40.5%	42.0%	42.0%	47.0%	34.4%	44.2%	44.2%	44.2%	44.2%	44.2%	44.2%	42.4%
Mitsubishi	17.6%	19.0%	19.0%	25.9%	17.9%	24.6%	24.6%	24.6%	24.6%	24.6%	24.6%	23.2%

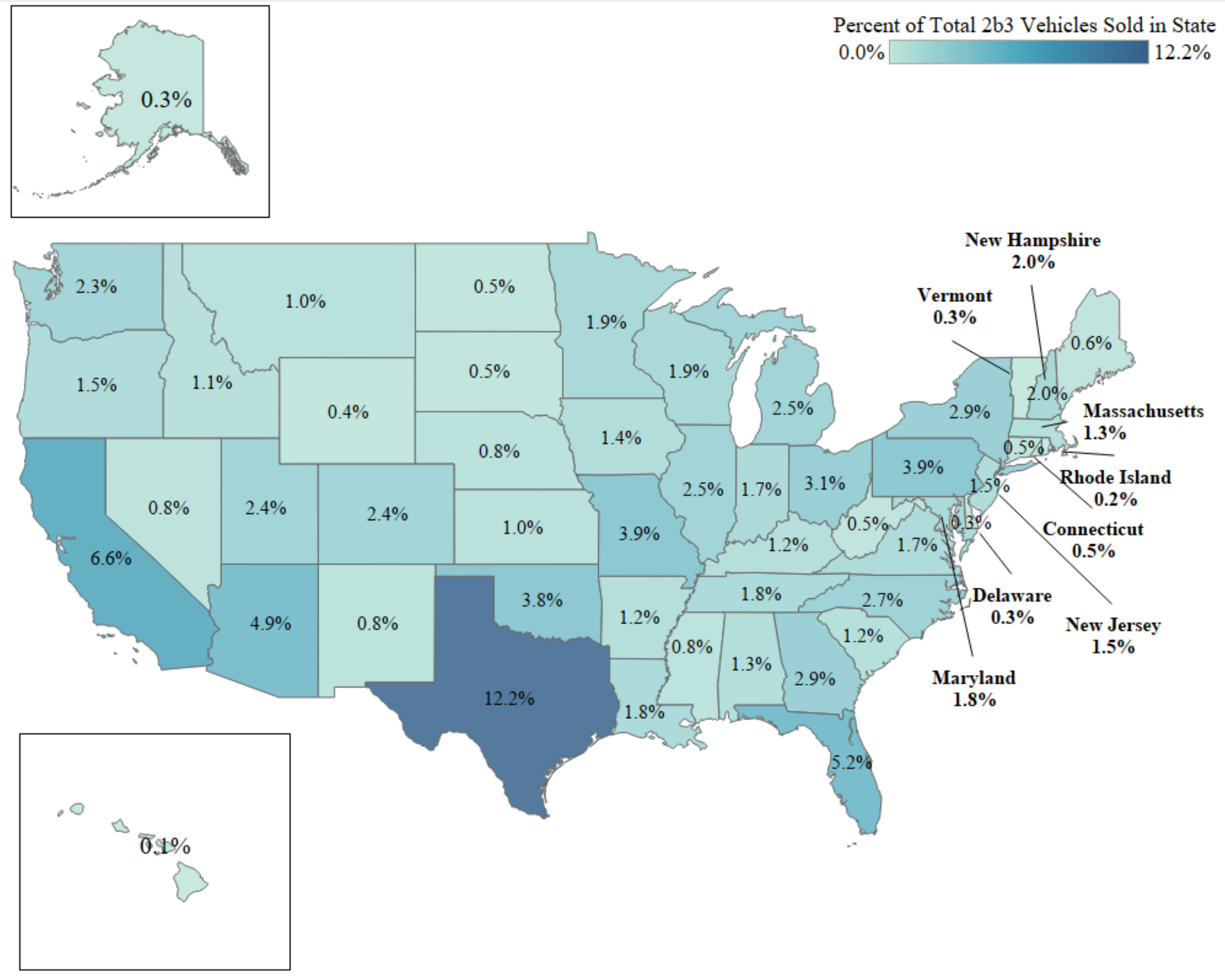
Percent of OEM Sales in ZEV States
16.8% 61.5%

2.5.1.2.1.2. Sales in ACT States

The ACT states (California, Colorado, Connecticut, Maryland, Massachusetts, New Jersey, New Mexico, New York, Oregon, Vermont, and Washington) comprise approximately 22% of the new Class 2b and 3 vehicle market in the U.S.[227] Figure 2-19 below shows the distribution of new model year 2021 sales of Class 2b and 3 vehicles across the U.S., as captured in the NVPP dataset.

[226] The figure ends with 2033 instead of 2035 because no changes in the ACC II state groups occur between 2033 and 2035.
[227] We consulted with Polk and determined that their NVPP data set that included vehicles in the 2b/3 weight class provided the most fulsome dataset at the time of analysis, recognizing that the 2b/3 weight class includes both 2b/3 heavy-duty pickups and vans and other classes within 2b/3 segment. While we determined that this dataset was the best option for the analysis, it does not contain all Class 3 pickups and vans sold in the United States.

Figure 2-19: Percent of Annual US Class 2b and 3 Vehicles Sold in Each State (MY 2021)



Overall, the manufacturers' shares of Class 2b and 3 sales in the eleven ACT states ranged from 18.7% to 42.8%. See Table 2-30 for the exact percent of national sales in ACT states sold by each manufacturer.

Table 2-30: MY 2021 Sales Share by Manufacturer in ACT States

2.5.1.2.1.3. Manufacturer	2.5.1.2.1.4. Percent of National Sales in ACT States
2.5.1.2.1.5. Mercedes-Benz	2.5.1.2.1.6. 42.8%
2.5.1.2.1.7. Stellantis	2.5.1.2.1.8. 23.4%
2.5.1.2.1.9. Ford	2.5.1.2.1.10. 22.0%
2.5.1.2.1.11. GM	2.5.1.2.1.12. 18.7%
2.5.1.2.1.13. Nissan	2.5.1.2.1.14. 24.6%

2.5.1.2.2. Estimating ZEV Credit Targets

We base the volumes used for the ZEV credit target calculation on each manufacturer's future assumed market share in ACC II and ACT states. We carry forward the market shares shown in Table 2-30 and Figure 2-18, calculated using NVPP data from model year 2021 as discussed in the previous subchapter, into future years. We examined market share data from model years 2016, 2019, and 2021 and determined that the geographic distribution of manufacturers' market shares remained fairly constant. Therefore, we determined that it was reasonable to carry forward the recently calculated market shares to future years.

The other inputs to calculating ZEV credit targets are the ZEV percentage requirement schedules and (in the case of ACT) truck class weight modifiers, and within the CAFE Model, estimated sales volumes for future model years by manufacturer and fleet.

2.5.1.2.2.1. ACC II Credit Targets

We calculate total credits required for ACC II and ACT compliance by multiplying the percentages from each program's ZEV requirement schedule by the ACC II or ACT state volumes by manufacturer, as seen in Equation 2-9 below. Figure 2-13 and Figure 2-16 show CARB's ACC II and ACT credit percentage requirements for each future year. Note that the light-duty ZEV percentage requirements change significantly after 2025, as the ACC II program begins in 2026 and has more stringent requirements than CARB's previous light-duty ZEV program.[228]

Equation 2-9: Required ZEV Credits Formula

$$ReqCredits_{M,MY} = SalesVol_{M,MY} * Mktshare_{M,MY} * ZEVPercent_{MY}$$

Where:

ReqCredits = Required credits

Sales Vol = National sales volumes

Mktshare = Share of sales in Section 177 states with ZEV standards

ZEVPercent = ZEV credit percentage requirement specified by CARB

M = Manufacturer

MY = Model Year

We then multiply the resulting national sales volume predictions by manufacturer by each manufacturer's total market share in the ACC II or ACT states to capture the appropriate volumes in the ZEV credits calculation. Required credits by manufacturer, per year, are determined within the CAFE Model by multiplying the ACC II state volumes by CARB's ZEV credit percentage requirement for each program, respectively.

2.5.1.2.2.2. ACT Credit Targets

The main difference between the credit calculations for ACT targets verses ACC II targets is the application of the vehicle class-specific weight modifier in the formula for ACT credit targets, as shown below in Equation 2-10.

Equation 2-10: ACT Required Credits Formula

$$ReqCredits_{M,MY}=SalesVol_{M,MY}*Mktshare_{M}*ZEVSalesPercent_{MY}*WeightModifier$$

Where:

ReqCredits = Required credits

Sales Vol = National sales volumes

Mktshare = Share of sales in Section 177 states with ZEV standards

[228] 13 CCR 1962.2(b); 13 CCR 1962.4.

ZEVSalesPercent = ZEV sales percentage requirement specified by CARB

WeightModifier = Weight modifier for Class 2b3 as specified by CARB (0.8)

M = Manufacturer

MY = Model Year

The weight modifier is the same for all heavy-duty pickup trucks and vans in our analysis, since all of those vehicles are in Class 2b and 3.

2.5.1.3. ZEV Candidates in the Analysis Fleet

The ZEV credit requirements estimated in the previous subchapter serve as a target for simulating ZEV compliance in all alternatives. As manufacturers can meet ACC II and ACT standards in a variety of different ways, using various technology combinations, NHTSA makes certain simplifying assumptions in choosing ZEV pathways, namely focusing on BEVs as ZEV candidates rather than PHEVs.

The CAFE Model calculates achieved credits by multiplying each ZEV's sales volume by the credits earned per vehicle, as stipulated by CARB's requirements and as discussed in Chapter 2.5.1. To ensure that the credit requirements are met, we add ZEV candidate vehicles to the reference baseline. ZEV candidates are flagged within the 'vehicles' worksheet in the Market Data Input File, which is described in Chapter 2.2. Although we identify the ZEV candidates in the CAFE Model Input File, the actual conversion from non-ZEV to ZEV vehicles occurs within the CAFE Model. The CAFE Model converts a vehicle to a ZEV during the specified ZEV application year.

We flag ZEV candidates in two ways: using reference vehicles with ICE powertrains or using PHEVs already in the existing fleet. For the first method, using reference vehicles, we identify these ZEV candidates by row, assign the relevant electrification technology level, and optionally specify the vehicle code of the reference vehicle. We identify all ICE vehicles with varying levels of technology (up to and including SHEVs) with rows that have 100 sales or more as ZEV candidates. All ZEV candidates become BEVs at the first opportunity, in model year 2023, which immediately follows the vintage of our analysis fleet. In the second method, for PHEV models identified as ZEV candidates, we base our determination of ZEV application years for each model based on expectations of manufacturers' future EV offerings. In the first method, the CAFE Model then moves the sales volume from reference vehicle row to the ZEV candidate row on an as-needed basis, considering the model year's ZEV credit requirements. For the PHEV models, the entire sales volume for that row is converted to BEV on the application year. This approach allows for only the needed additional sales volumes to flip to ZEVs, based on the ACC II and ACT targets, and keeps us from overestimating ZEVs in future years.

See Chapter 2, S5.9 - ZEV Credits and Compliance in the CAFE Model Documentation for further information regarding the model's treatment of ZEV candidates.

2.5.1.3.1. Light-duty ZEV Candidates

NHTSA identifies light-duty ZEV candidates by duplicating every row with 100 or more sales that is not a PHEV, BEV, or FCEV. We refer to the original rows as 'reference vehicles.' Although PHEVs[229] are all ZEV candidates, we do not duplicate those rows as we focus the CAFE Model's simulation of the ACC II and ACT programs on BEVs. However, any PHEVs already in the analysis fleet or made by the model will still receive the appropriate ZEV credits. While flagging the ZEV candidates, we identified each one as either a BEV1, BEV2, BEV3, or BEV4 (i.e., BEV technology types based on range) based partly on their price, market segment, and vehicle features. For instance, we assumed luxury cars would have longer ranges than economy cars. We also assigned AWD/4WD variants of vehicles shorter BEV ranges when appropriate. See Chapter 3.3 for more detailed information on electrification options for this analysis.

[229] The CAFE Model has several technologies labeled PHEV20s and PHEV50s in the analysis fleet. (See Chapter 3 for discussion of electrification technologies).

The CAFE Model assigns credit values per vehicle depending on whether the vehicle is a ZEV in a model year prior to 2026 or after, due to the change in value after the update of the standards from ACC II. For model years 2022-2025, when the ACC I program rules are in place, PHEV20s earn 0.7 credits and PHEV50s earn 1.0 credit. Only the PHEV50s earn partial vehicle credits for the ACC II program in 2026 and beyond, as the PHEV20s do not meet the AER requirements for partial vehicle credits. PHEV50s have greater than 40 miles AER on the US06 cycle and greater than 70 miles on the combined certification test. As a simplifying assumption, we assume that all PHEV50s can receive the full 1.0 credit in 2026 and beyond. As stated previously, we do not convert any vehicles to PHEVs in the ZEV modeling. The only PHEVs that will receive credit are PHEV50s already existing in the analysis fleet and those built by the model independently from the ZEV modeling in the reference baseline.

In model years when the ACC I program is in place (2022-2025), BEVs earn between 2.5 and 4.0 credits, depending on the range. From model years 2026 onward, all BEVs each earn 1.0 credit.

2.5.1.3.2. HDPUV ZEV Candidates

NHTSA follows a similar process in assigning HDPUV ZEV candidates as done in assigning light-duty ZEV candidates. We duplicate every van row with 100 or more sales and duplicate every pickup truck row with 100 or more sales, provided the vehicle model has a work factor less than 7,500 and a diesel- or gasoline-based range lower than 500 miles (based on their rated fuel economy and fuel tank size). This is consistent with our treatment of HDPUVs in the technology pathways, which is discussed in Chapter 3.3. Note that the model can still apply PHEV technology to HDPUVs. When identifying ZEV candidates, we assign each candidate as either a BEV1 or a BEV2 based on their price, market segment, and other vehicle attributes. HDPUV PHEVs receive 0.75 credits and full ZEVs receive 0.8 credits.

2.5.2. Inflation Reduction Act Tax Credits

2.5.2.1. Overview of Tax Credits in the Inflation Reduction Act

NHTSA explicitly models several aspects of the Inflation Reduction Act (IRA) Tax Credits when simulating the behavior of manufacturers and consumers. NHTSA includes these incentives in modeling the reference baseline and action alternatives.[230] The first aspect modeled is the Advanced Manufacturing Production Credit (AMPC). This provision of the IRA provides a $35 per kWh tax credit for manufacturers of battery cells and an additional $10 per kWh for manufacturers of battery modules manufactured in the United States.[231] The AMPC tax credits phase out from 2030 to 2032. To qualify to for the $35 per kWh credit, battery cells must store at least 12 watt-hours of energy. Battery modules must have an aggregate capacity of at least 7 kWh (1kWh for FCEVs) to qualify for the $10 per kWh module credit. As a result, the CAFE Model assumes only batteries for PHEVs, BEVs, and FCVs qualify and excludes HEVs.

For the Final Rule, NHTSA is jointly modeling two IRA tax credits available at the time of first sale. Similar to the proposal, the first of these tax credits is the Clean Vehicle Credit (§ 30D),[232] which provides up to $7,500 toward the purchase of clean vehicles with critical minerals extracted or processed in the U.S. or countries with which the U.S. has a free trade agreement (or recycled in North America), and battery components manufactured in North America.[233] This credit is available for PHEVs, BEVS, and FCEVs with MSRPs below

[230] Given that electrification cannot be used as a compliance pathway in standard setting years and the tax credits phase-out by 2032, the majority of the influence of tax credits are captured within the baseline.
[231] 26 USC 45X. If a manufacturer produces a battery module without battery cells, they are eligible to claim up to $45 per kWh for the battery module. Two other provisions of the AMPC are not modeled at this time; (i) a credit equal to 10 percent of the manufacturing cost of electrode active materials, (ii) a credit equal to 10 percent of the manufacturing cost of critical minerals for battery production. We are not modeling these credits directly because of how we estimate battery costs and to avoid the potential to double count the tax credits if they are included into other analyses that feed into our inputs. We chose not to model these components for several reasons. Unlike the CVC's critical mineral requirements, which allows vehicles whose minerals are produced or processed in foreign nations with free trade agreements with the United States to qualify, the AMPC requires eligible components to be produced within the United States. The preponderance of component materials are mined outside of the United States. While we suspect the AMPC, coupled with other incentives, will induce development domestically, it will take years for the full impact of these efforts to come to fruition in regard to mineral production. Even when these capabilities are realized, the amount produced domestically is projected to be a minority of the total minerals produced. Given the growing demand for these minerals will continue to increase globally as the demand for electrified vehicles and other clean energy products increases, the timing and impact of the AMPC on domestic electric vehicle prices is highly uncertain.
[232] 26 USC 30D.
[233] There are vehicle price and consumer income limitations on the CVC, as well. See Congressional Research Service. 2022. Tax Provisions in the Inflation Reduction Act of 2022 (H.R. 5376). Available at: https://crsreports.congress.gov/product/pdf/R/R47202/6. (Accessed: May 31, 2023).

$55,000 for cars and $80,000 for vans, SUVs, and pickups. Buyer eligibility for § 30D depends on income level. Buyer eligibility is dependent on income levels for the credit offered in § 30D. The second credit, which is new to the analysis, is the Credit for Qualified Commercial Clean Vehicles (§ 45W), which provides up to $7,500 toward the purchase of a vehicle with a GVWR of less than 14,000 pounds by a commercial entity for a purpose other than resale, and up to $40,000 for heavier vehicles.[234] The credit value is the lesser of the incremental cost to purchase a comparable ICE vehicle or 15 percent of the cost basis for PHEVs or 30 percent of the cost basis for FCVs and BEVs. Among other requirements, a qualified commercial clean vehicle must be acquired for use or lease by the taxpayer and not for resale. The credit may be available to a lessor that is leasing personal vehicles.[235] Vehicles may be eligible for § 30D or § 45W credit (collectively, CVC) if placed in service before the end of 2032, and only one of the CVCs can be claimed for any given purchase.

2.5.2.2. Simulating Market Response to a Tax Credit

The market mechanism where consumers shop on price, and producers seek market share by undercutting competitors' prices, tends to ensure that subsidies like the AMPC and the CVCs, regardless of whether they are initially paid to producers or consumers, are ultimately shared between the two groups. Only in cases where suppliers' or buyers' behavior is extremely inflexible (i.e., supply or demand is highly "inelastic" with respect to prices) will one or the other "capture" most or all of the subsidy. While a complete analysis of the ultimate incidence of the tax credits would involve estimating vehicle model or class-specific price elasticities of demand and supply and using these to estimate changes in prices and quantities for eligible vehicles, the simplified examples below show that its general results will depend on the relative elasticity of demand and supply to changes in prices of the models that are subsidized.

The results of that analysis would be sensitive to the relative elasticities of supply and demand. If demand is relatively elastic and supply inelastic, you would expect small changes in quantities and the tax credit would function primarily as a transfer from taxpayers to EV producers. A tax subsidy drives a wedge between the effective price producers receive and the effective price the consumer pays, similar to the effect of an excise tax. This case is shown in Figure 2-20, where demand shifts from D1 to D2, and consumers see a small reduction in prices from P_c to P_{c2} while producers see a much larger increase in the producer price from P_s to P_{s2}, and sales shift only slightly from Q1 to Q2.[236]

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[234] 26 USC 45W.

[235] *See*, *e.g.*, https://www.irs.gov/pub/taxpros/fs-2023-04.pdf.

[236] The economic theory demonstrated graphically in this subchapter can also be demonstrated mathematically. We present the competitive market case here. The supply, q_s, and demand q_d, equations ($B < 0$, $b > 0$, $a < A$) are:

$$q_s = a + bp \quad ; \quad q_d = A + Bp$$

In equilibrium qs = qd, and the market price is:

$$p = \frac{a-A}{B-b}$$

If a subsidy of $x > 0$ per unit sold is given to the supplier, the equilibrium market price is found by solving:

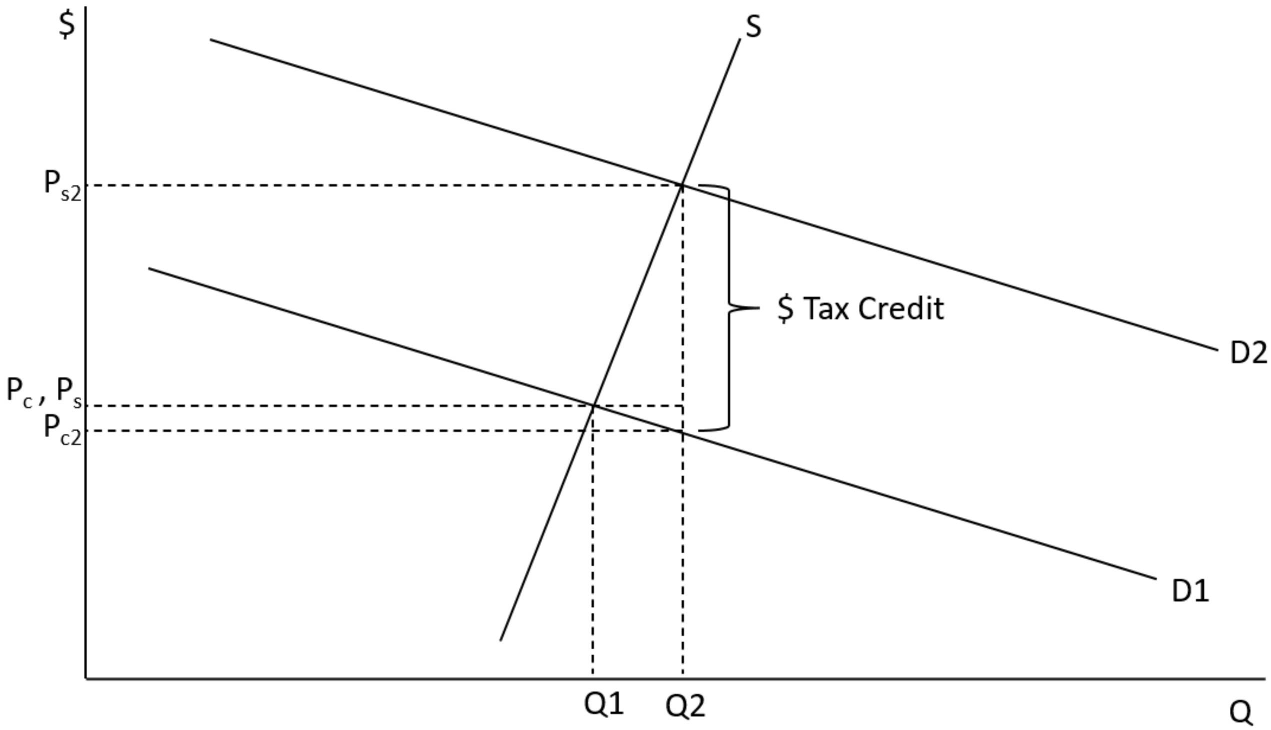
$$q_s = a + b(p+x) = A + Bp = q_d$$
$$p = \frac{a-A+bx}{B-b} = \frac{a-A}{B-b} + \frac{b}{B-b}x$$

The market price is reduced by x[b/(B-b)]. While the price is reduced by xb/(B-b), the supplier gets x[1+b/(B-b)] = xB/(B-b). The consumer gets the price reduction of xb/(B-b). Each gets half of x when B = -b.

The same reasoning applies if the subsidy is given to the consumer:

$$q_d = A + B(p-x) = a + bp = q_s$$

Figure 2-20: Elastic Demand, Inelastic Supply



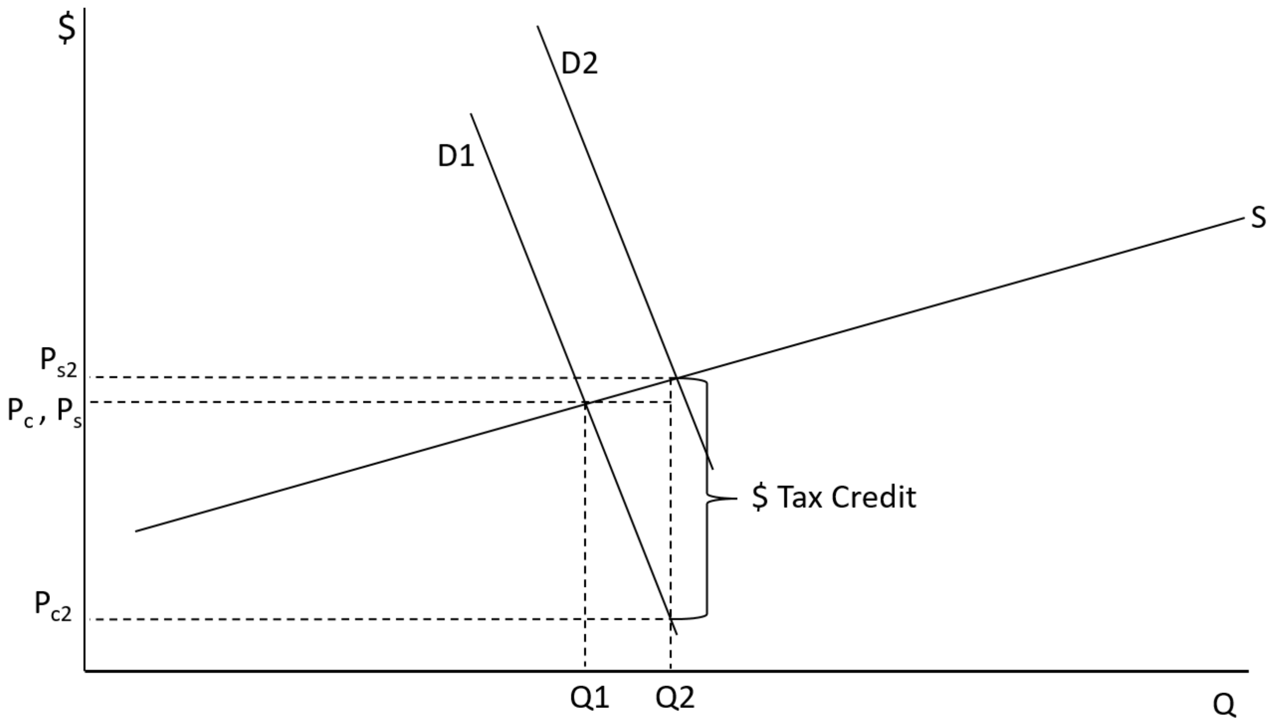
If demand for EVs is highly inelastic and supply of EV is highly elastic, the increase in EV quantities would be modest and the tax credit would primarily be a transfer of taxpayers money by the government to EV consumers. This is shown in Figure 2-21, where consumers see a large reduction in the effective price they pay (again from P_c to P_{c2}), while producers see only a small increase in the price they receive (from P_s to P_{s2}). Importantly, sales shift only modestly from Q1 to Q2.

$$p=\frac{A-Bx-a}{b-B}=\frac{a-A}{B-b}+\frac{B}{B-b}x$$

In this case, B/(B-b) > 0, so the market equilibrium price goes up by xB/(B-b) but the consumer keeps xb/(B-b), just as in the case where the supplier gets the subsidy.

Because the price elasticities of supply and demand are equal to the price coefficients (b and B) times the ratio of price to quantity (p/qs, p/qd), and because in equilibrium supply = demand, the same ratios of price coefficients apply to ratios of elasticities. In terms of elasticities of demand (βd) and supply (βs), the subsidy x, is shared x(βs/(βd – βs)) to the consumer and x(βd/(βd – βs)) to the producer. Again, the sharing is 50/50 if βd = – βs.

Figure 2-21: Elastic Supply, Inelastic Demand



In both Figure 2-20 and Figure 2-21, the market participants (producers or consumers) whose behavior is less price elastic are ultimately able to capture a larger fraction of the tax credit, and hence will experience the bulk of the benefit of the tax credit transfer. However, in cases where the elasticities of supply and demand are similar in magnitude, the tax credit will be shared more equally, while the magnitude of the change in sales varies depending on whether both demand and supply are both inelastic, both elastic, or somewhere between those extremes. Figure 2-22 shows the scenario where both supply and demand are inelastic and the sales response is small, while Figure 2-23 illustrates the case where both supply and demand are price-elastic, and the resulting sales response is large.

Figure 2-22: Inelastic Supply, Inelastic Demand

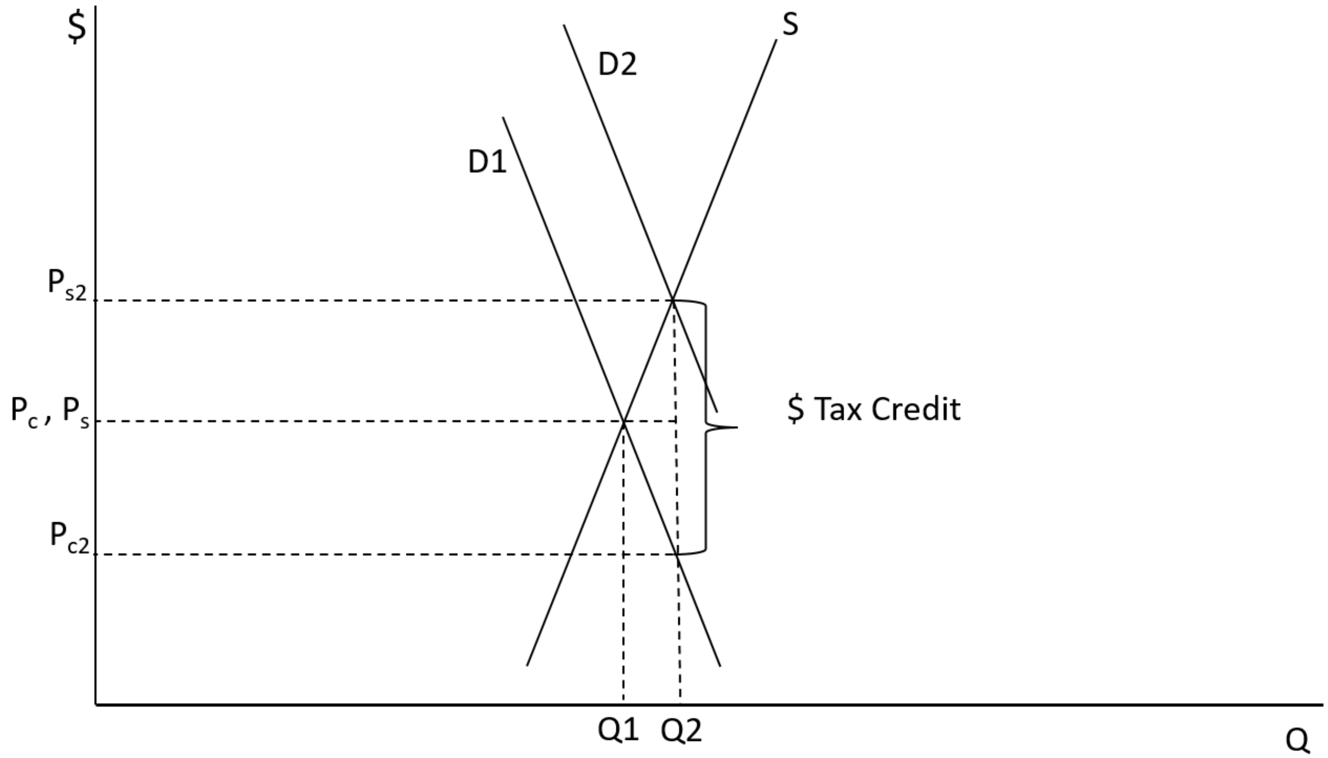
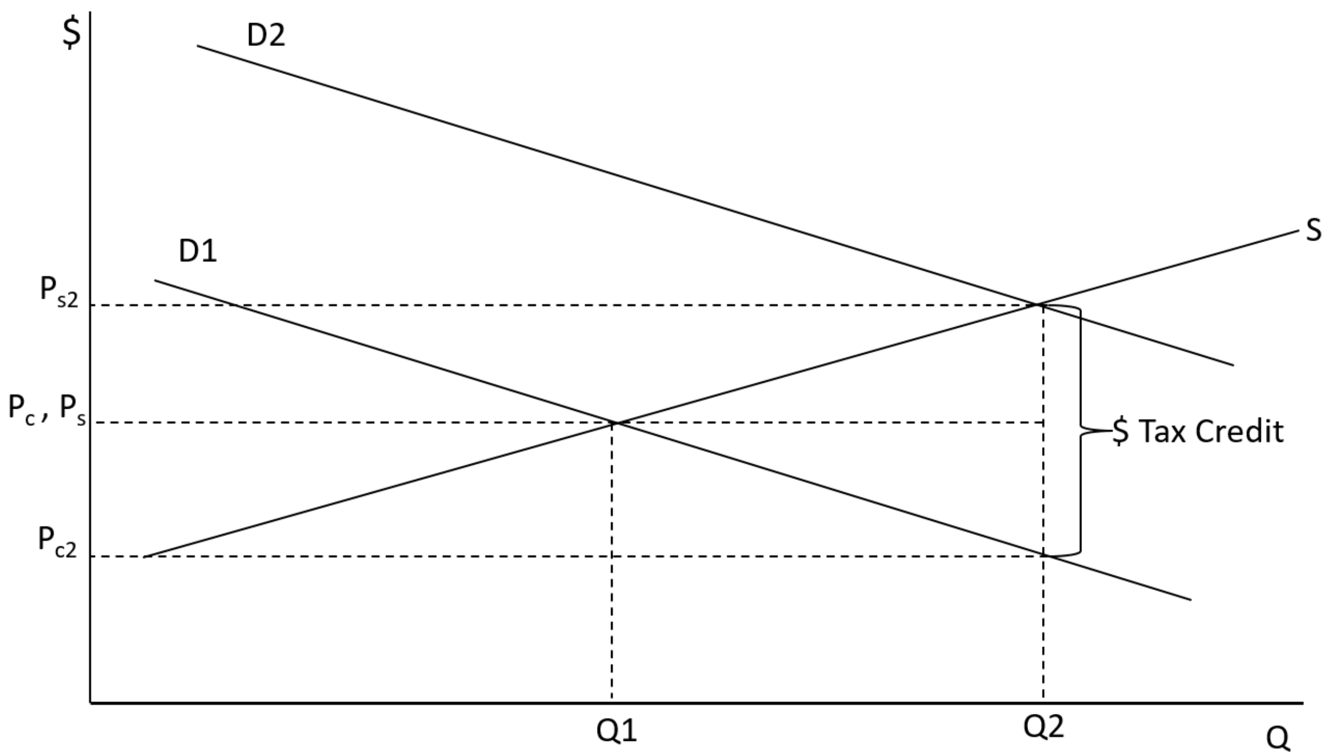


Figure 2-23: Elastic Supply, Elastic Demand



2.5.2.3. Implementation of the AMPC and the CVCs

While the model simulates fuel economy improvements and changes in production costs at the vehicle model level, it does not analyze changes in prices or sales at that same level of detail, and in any case the agency does not have access to the detailed price elasticities of demand and supply for individual models that would be required to do so. NHTSA did not implement the detailed market process described in the previous subchapter within its CAFE Model. Instead, the agency first assumes that manufacturers and consumers each capture half of the dollar value available to the market of the AMPC and CVCs. Second, the agency assumes that manufacturers' shares of both credits will offset part of their incremental costs to add models that are eligible for the credits —PHEVs, BEVs, and FCVs—to their product offerings. Both credits apply to both light-duty vehicles and HDPUVs covered by this rule.

The CAFE Model's approach to analyzing the effects of the AMPC and the CVCs includes several other restrictions, due to the terms of the two credits and the structure of the CAFE Model itself. The CAFE Model accounts for the MSRP restrictions of § 30D by assuming that it cannot be applied to passenger cars with an MSRP above $55,000 or other vehicles with an MSRP above $80,000, since these are ineligible for the tax credit. NHTSA cannot explicitly represent the income restrictions of § 30D in its analysis because the CAFE Model does not account for purchasers' income, and in any case, we do not have reliable data on the income levels of consumers purchasing specific vehicle brands and models. However, the agency's procedure for modeling MSRP restrictions partially captures § 30D income thresholds indirectly, insofar as high-income buyers are more likely to purchase luxury vehicles that exceed the § 30D's MSRP caps. NHTSA notes that the § 45W does not feature these restrictions but unlike 30D, it is available only to businesses and tax-exempt organizations (which includes firms that obtain vehicles to lease them as personal vehicles). While the limitations under § 30D and § 45W differ with respect to MSRP caps, the total incentive values for the CVCs is based on the assumption that the majority of vehicles will be eligible under § 30D. Because the CAFE model cannot distinguish between 30D and 45W eligibility, the analysis applies the MSRP caps to all vehicles.

Nor does NHTSA's analysis explicitly represent any of the tax credits' accompanying restrictions on the location of final assembly and battery production or the origin of critical minerals at a model specific level. While the labor component of this analysis makes certain assumptions about the location of vehicle production, we do not have a reliable method or source to estimate where production is likely to occur during future model years, particularly as manufacturers respond to the provisions of the IRA. DOE provided analysis, however, that estimates the average tax credits for personal vehicles over time based on a variety of factors. Except for models that do not meet the MSRP limits, we assume that all PHEVs, BEVs, and FCVs produced and sold during the time frame that tax credits are offered will receive the respective fleet and powertrain average credit provided in the DOE analysis, described below.

The AMPC credit scales with battery capacity. To determine powertrain average credits, NHTSA staff determined average battery energy capacity by powertrain (e.g., PHEV, BEV, FCEV) for passenger cars, light trucks, and HDPUVs based on Argonne simulation outputs, and these estimates are reported in Table 2-31.[237]

Table 2-31: Assumed Vehicle Battery Capacities for AMPC in kWh

Powertrain Type	Passenger Car	Light Truck	HDPUV
PHEV	21	34	51
BEV	83	121	134
FCV	1	1	2

NHTSA recognizes that domestic production of eligible technologies for the AMPC may take time to ramp-up over the coming years. As a result, not all vehicles are likely to benefit from the tax credit in its earlier years as the agency's analysis implicitly assumes. To reflect this ramp-up, we reduce the modeled value of the AMPC in its first few years of availability. We chose a linear ramp of 20 percent per year starting in model

[237] Capacity estimates are based on Argonne vehicle types: midsize car (passenger car), non-performance pickups (LT), and 2b3 (HDPUV). Powertrain types are based on: BEV300, PHEV50PS (midsize), ParPHEV50 (pickup), and Fuel Cell EV for LD; BEV1, ParPHEV, and FCV for HDPUV.

year 2023 until the credit is maximized for model year 2027. The AMPC then phases out gradually beginning in model year 2030 and is eliminated after model year 2032.[238] Table 2-31 shows the assumed nominal and constant 2021 dollar value of the AMPC per kWh by model year. The energy capacity values in Table 2-31 and credit values in Table 2-32 combine to produce total AMPC amounts by vehicle type in the CAFE Model's Scenarios Input File.

Table 2-32: Tax Credit Values per kWh for the Advanced Manufacturing Production Credit[239]

Model Year	Nominal $/kWh	Real $2021/kWh
2023	9	8
2024	18	16
2025	27	23
2026	36	30
2027	45	37
2028	45	36
2029	45	35
2030	34	26
2031	23	17
2032	11	8
2033	0	0

For the Final Rule, NHTSA uses projected combined values of the CVCs provided by the US Department of Energy. These values consider the latest information of EV penetration rates, EV retail prices, the share of US EV sales that meet the critical minerals and battery component requirements of § 30D, the share of vehicles that exclude suppliers that are "Foreign Entities of Concern" as required by § 30D, and lease rates for vehicles that qualify for the § 45W CVC.[240] These values are informed by the best available information and represent an improvement on the assumed ramp rate NHTSA used at the proposed rule stage. Table 2-33 shows the nominal and 2021 constant dollar values that NHTSA uses in the Final Rule analysis.

Table 2-33: Tax Credit Values for the Clean Vehicle Credit[241]

Model Year	Nominal $/vehicle	Real $2021/vehicle
2023	3,900	3,493
2024	4,200	3,672
2025	4,400	3,765
2026	4,400	3,686
2027	4,800	3,936
2028	5,000	4,014

[238] For this Final Rule, NHTSA assumed that vehicles in a given model year are eligible for credits availble in the same calendar year.
[239] Nominal values in future years are converted to constant 2021 dollars using the ratio of the GDP delfator in 2021 and the projected GDP deflator in the model year. Projections are taken from the 2023 AEO Reference Case Table 20. Macroeconomic Indicators. Available at: https://www.eia.gov/outlooks/aeo/data/browser/#/?id=18-AEO2023&cases=ref2023&sourcekey=0 (Accessed: April 25, 2024).
[240] U.S. Department of Energy. 2024. Estimating Tax credits for Heavy Duty Electric Vehicle Infrastructure and for Acquiring Electric Vehicles Weighing Less Than 14,000 Pounds. Mar. 11, 2024.
[241] Nominal values in future years are converted to constant 2021 dollars using the ratio of the GDP delfator in 2021 and the projected GDP deflator in the model year. Projections are taken from the 2023 AEO Reference Case Table 20. Macroeconomic Indicators. Available at: https://www.eia.gov/outlooks/aeo/data/browser/#/?id=18-AEO2023&cases=ref2023&sourcekey=0 (Accessed: April 25, 2024).

2029	5,200	4,085
2030	5,500	4,226
2031	5,800	4,357
2032	6,000	4,406
2033	0	0

Importantly, due to EPCA's constraints on considering the fuel economy of dedicated alternative fuel automobiles in determining maximum feasible standards, NHTSA does not permit the model to add BEVs during the standard setting years except in response to the ZEV program and manufacturer deployment commitments. The effect of the tax credits on BEV adoption in our analysis will be to add those vehicles if cost effective until the standard setting years in model year 2027 but will have no effect thereafter. Dual-fueled vehicles such as PHEVs may still be added during the standard setting years if they are cost effective when considering their operation solely on gasoline or charge sustaining mode. The impact of the tax credits on PHEVs in our analysis shows that as manufacturers retain higher tax credits, the PHEVs as a fraction of total sales increase in both the No-Action Alternative and action alternatives.

2.6. Technology Applicability Rules

As discussed in Chapter 2.2, starting with a fixed analysis fleet, the CAFE Model estimates ways each manufacturer could potentially apply specific fuel-saving technologies to specific vehicle model/configurations in response to, among other things (such as fuel prices), CAFE standards, CO_2 standards, commitments some manufacturers have made to CARB's Framework Agreement, and ZEV programs imposed by California and several other states. The CAFE Model follows a year-by-year approach to simulating manufacturers' potential decisions to apply technology, accounting for multiyear planning within the context of estimated schedules for future vehicle redesigns and refreshes during which significant technology changes may most practicably be implemented.

The modeled technology adoption for each manufacturer under each regulatory alternative depends on this representation of multiyear planning, and on a range of other factors represented by other model characteristics and inputs, such as inputs directing the model to "skip" specific technologies for specific vehicle model/configurations in the analysis fleet (e.g., because manufacturers already heavily invested in engine turbocharging and downsizing are unlikely to abandon this approach in favor of using high compression ratios); inputs defining the sharing of engines, transmissions, and vehicle platforms in the analysis fleet; the model's logical approach to preserving this sharing; and the logical progression of technologies defined by the model's technology pathways.

The "skip" input – represented in the Market Data Input File as "SKIP" in the appropriate technology column corresponding to a specific vehicle model – is particularly important for accurately representing how a manufacturer applies technologies to their vehicles in the real world. As mentioned above, this tells the model not to apply a specific technology to a specific vehicle model. By capturing these real-world processes and decision making, we can ensure that modeling appropriately captures the relative costs and benefits for applying different levels of fuel economy-improving technology. Skip inputs are used to simulate manufacturer decisions with cost-benefit in mind, including (1) parts and process sharing; (2) stranded capital; and (3) performance neutrality.

First, parts sharing includes the concepts of platform, engine, and transmission sharing, which are discussed in detail in Market Data Input File subchapter, above. A "platform" refers to engineered underpinnings shared on several differentiated vehicle models and configurations. Manufacturers share and standardize components, systems, tooling, and assembly processes within their products (and occasionally with the products of another manufacturer) to manage complexity and costs for development, manufacturing, and assembly. Detailed discussion for this type of SKIP is provided in the "adoption features" section for different technologies, if applicable, in Chapter 3.

Similar to vehicle platforms, manufacturers create engines that share parts. For instance, manufacturers may use different piston strokes on a common engine block or bore out common engine block castings with different diameters to create engines with an array of displacements. Head assemblies for different displacement engines may share many components and manufacturing processes across the engine family. Manufacturers may finish crankshafts with the same tools to similar tolerances. Engines on the same architecture may share pistons, connecting rods, and the same engine architecture may include both six- and eight-cylinder engines. One engine family may appear on many vehicles on a platform, and changes to that engine may or may not carry through to all the vehicles. Some engines are shared across a range of different vehicle platforms. Vehicle model/configurations in the analysis fleet that share engines belonging to the same platform are identified as such, and we also may apply a SKIP where we know that a manufacturer shares an engine throughout several of their vehicle models.

It is important to note that manufacturers define common engines differently. Some manufacturers consider engines as "common" if the engines share an architecture, components, or manufacturing processes. Other manufacturers take a narrower definition, and only assume "common" engines if the parts in the engine assembly are the same. In some cases, manufacturers designate each engine in each application as a unique powertrain. For example, a manufacturer may have listed two engines separately for a pair that share designs for the engine block, the crank shaft, and the head because the accessory drive components, oil pans, and engine calibrations differ between the two. In practice, many engines share parts, tooling, and assembly resources, and manufacturers often coordinate design updates between two similar engines. We consider engines together (for purposes of coding, discussed in Chapter 2.2 above, and for SKIP application) if the engines share a common cylinder count and configuration, displacement, valvetrain, and fuel type, or if the engines only differed slightly in compression ratio, HP, and displacement.

Parts sharing also includes the concept of sharing manufacturing lines (the systems, tooling, and assembly processes discussed above), since manufacturers are unlikely to build a new manufacturing line to build a completely new engine. A new engine that is designed to be mass manufactured on an existing production line will have limits in number of parts used, type of parts used, weight, and packaging size due to the weight limits of the pallets, material handling interaction points, and conveyance line design for a manufacturer designated takt time. The restrictions will be reflected in the usage of a skip of engine technology that the manufacturing line would not accommodate.

SKIPs also relate to instances of stranded capital when manufacturers amortize research, development, and tooling expenses over many years, especially for engines and transmissions. The traditional production life-cycles for transmissions and engines have been a decade or longer. If a manufacturer launches or updates a product with fuel-saving technology, and then later replaces that technology with an unrelated or different fuel-saving technology before the equipment and research and development investments have been fully paid off, there will be unrecouped, or stranded, capital costs. Quantifying stranded capital costs accounts for such lost investments. One design where manufacturers take an iterative redesign approach, as described in a recent SAE paper,[242] is the MacPherson strut suspension. It is a popular low-cost suspension design and manufacturers use it across their fleet.

As we observed previously, manufacturers may be shifting their investment strategies in ways that may alter how stranded capital could be considered. For example, some suppliers sell similar transmissions to multiple manufacturers. Such arrangements allow manufacturers to share in capital expenditures or amortize expenses more quickly. Manufacturers share parts on vehicles around the globe, achieving greater scale and greatly affecting tooling strategies and costs.

As a proxy for stranded capital in recent CAFE analyses, the CAFE Model has accounted for platform and engine sharing and includes redesign and refresh cycles for significant and less significant vehicle updates. This analysis continues to rely on the CAFE Model's explicit year-by-year accounting for estimated refresh and redesign cycles, and shared vehicle platforms and engines, to moderate the cadence of technology adoption and thereby limit the implied occurrence of stranded capital and the need to account for it explicitly. In addition, confining some manufacturers to specific advanced technology pathways through technology adoption features acts as a proxy to indirectly account for stranded capital. Adoption features specific to each

[242] Pilla, S. et al. 2021. Parametric Design Study of McPherson Strut to Stabilizer Bar Link Bracket Weld Fatigue Using Design for Six Sigma and Taguchi Approach. SAE Technical Paper 2021-01-0235. Available at: https://www.sae.org/publications/technical-papers/content/2021-01-0235/. (Accessed: May 31, 2023).

technology, if applied on a manufacturer-by-manufacturer basis, are discussed in each technology subchapter. We will monitor these trends to assess the role of stranded capital moving forward.

Finally, we ensure that our analysis is performance neutral because the goal is to capture the costs and benefits of adding fuel economy-improving technology *because* of the regulations,[243] and not to inappropriately capture costs and benefits for changing other vehicle attributes that may have a monetary value associated with them.[244] This means that we "SKIP" some technologies where we can reasonably assume that the technology would not be able to maintain a performance attribute for the vehicle, and where our simulation over test cycles may not capture the technology limitation. For example, prior to the development of SAE J2807, manufacturers used internal rating methods for their vehicle towing capacity. Manufacturers switched to the SAE tow rating standard at the next redesign of their respective vehicles so that they could mitigate costs via parts sharing and remain competitive in performance. Usually, the most capable powertrain configuration will also have the highest towing capacity and can be reflected in using this input feature. Separately, we also ensure that the analysis is performance neutral through other inputs and assumptions, like developing our engine maps assuming use with a fuel grade most commonly available to consumers.[245,246] Those assumptions are discussed throughout this chapter and Chapter 3.

Other factors represented by model characteristics and inputs include the technologies already present in the analysis fleet; inputs defining each regulatory alternative's specific requirements; inputs defining expected future fuel prices, annual mileage accumulation, and valuation of avoided fuel consumption; and inputs defining the estimated efficacy and future cost (accounting for projected future "learning" effects) of included technologies; inputs controlling the maximum pace the simulation is to "phase in" each technology; and inputs further defining the availability of each technology to specific technology classes.

Two of these inputs—the "phase-in cap" and the "phase-in start year"—apply to the manufacturer's entire estimated production and, for each technology, define a share of production in each model year that, once exceeded, will stop the model from further applying that technology to that manufacturer's fleet in that model year. The influence of these inputs varies with regulatory stringency and other model inputs. For example, setting the inputs to allow immediate 100 percent penetration of a technology will not guarantee any application of the technology if stringency increases are low and the technology is not at all cost effective. Also, even if these are set to allow only very slow adoption of a technology, other model aspects and inputs may nevertheless force more rapid application than these inputs, alone, would suggest (e.g., because an engine technology propagates quickly due to sharing across multiple vehicles, or because BEV application

[243] One example is GM's 2nd generation High Feature V6 engine manufactured at their Romulus, MI plant (https://www.gm.com/company/facilities/romulus). These engines are represented by engine codes 113601, 113602, 113603 and should all be skipped for HCR due to 113603 being a pickup engine on the GMC Canyon and Chevrolet Colorado. DOT staff will add these skips for the final rule.

[244] *See*, e.g., 87 FR 25887, citing EPA. 2018. Consumer Willingness to Pay for Vehicle Attributes: What is the Current State of Knowledge? EPA-420-R-18-016. Available at: https://cfpub.epa.gov/si/si_public_record_report.cfm?Lab=OTAQ&dirEntryId=339388 ("The agency has previously attempted to model the potential opportunity cost associated with changes in other vehicle attributes in sensitivity analyses. In those other rulemakings, the agency acknowledged that it is extremely difficult to quantify the potential changes to other vehicle attributes. To accurately do so requires extensive projections about which and how much of other attributes will be altered and a detailed accounting of how much value consumers assigned to those attributes. The agency modeled the opportunity cost associated with changes in other vehicle attributes using published empirical estimates of tradeoffs between higher fuel economy and improvements to other attributes, together with estimates of the values buyers attach to those attributes. The agency does not believe this is an appropriate methodology since there is considerable uncertainty in the literature about how much fuel economy consumers are willing to pay for and how consumers value other vehicle attributes. We note, for example, a recent EPA-commissioned study that "found very little useful consensus" regarding "estimates of the values of various vehicle attributes," which ultimately were "of little use for informing policy decisions."").

[245] *See*, e.g., 85 FR 24386 ("Vehicle manufacturers typically develop their engines and engine control system calibrations based on the fuel available to consumers. In many cases, manufacturers may recommend a fuel grade for best performance and to prevent potential damage. In some cases, manufacturers may require a specific fuel grade for both best performance, to achieve advertised power ratings, and/or to prevent potential engine damage. Consumers, though, may or may not choose to follow the manufacturer's recommendation or requirement for a specific fuel grade for their vehicle. As such, vehicle manufacturers often choose to employ engine control strategies for scenarios where the consumer uses a lower than recommended, or required, fuel octane level, as a way to mitigate potential engine damage over the life of a vehicle. These strategies limit the extent to which some efficiency improving engine technologies can be implemented, such as increased compression ratio and intake system and combustion chamber designs that increase burn rates and rate of in-cylinder pressure rise. If the minimum octane level available in the market were higher (especially the current sub-octane regular grade in the mountain states), vehicle manufacturers might not feel compelled to design vehicles sub-optimally to accommodate such blends.").

[246] *Id.* At 24390 ("As described in the NPRM and PRIA, the agencies developed engine maps for technologies that are in production today or that are expected to be available in the rulemaking timeframe. The agencies recognize that engines with the same combination of technologies produced by different manufacturers will have differences in BSFC and other performance measures, due to differences in the design of engine hardware (*e.g.,* intake runners and head ports, valves, combustion chambers, piston profile, compression ratios, exhaust runners and ports, turbochargers, etc.), control software, and emission calibration. Therefore, the engine maps are intended to represent the levels of performance that can be achieved on average across the industry in the rulemaking timeframe.").

must increase quickly in response to ZEV requirements). For this analysis, nearly all of these inputs are set at levels that do not limit the simulation at all.

As discussed below in Chapter 3.1, for the most advanced engines (ADEAC, variable compression ratio, variable turbocharger geometry, and turbocharging with DEAC), DOT has specified phase-in caps and phase-in start years that limit the pace at which the analysis shows the technology being adopted in the rulemaking timeframe. For example, this analysis applies a 34 percent phase-in cap and model year 2019 phase-in start year for ADEAC, meaning that in model year 2021 (using a model year 2020 fleet, the analysis begins simulating further technology application in model year 2021), the model will stop adding ADEAC to a manufacturer's model year 2021 fleet once ADEAC reaches more than 68 percent penetration, because 34% x (2021 – 2019) = 34% x 2 = 68%.

As discussed in Chapter 3.3, this analysis also applies phase-in caps and corresponding start years to prevent the simulation from showing unlikely rates of applying BEVs, such as showing that a manufacturer producing very few BEVs in model year 2022 could plausibly replace every product with a 300- or 400-mile BEV by model year 2026. Also, as discussed in Chapter 3.4, this analysis applies phase-in caps and corresponding start years intended to ensure that the simulation's plausible application of the highest included levels of MR (20 percent reductions of vehicle "glider" weight) do not, for example, outpace plausible supply of raw materials and development of entirely new manufacturing facilities.

These model logical structures and inputs act together to produce estimates of ways each manufacturer could potentially shift to new fuel-saving technologies over time, reflecting some measure of protection against rates of change not reflected in, for example, technology cost inputs. This does not mean that every modeled solution would necessarily be economically practicable. Using technology adoption features like phase-in caps and phase-in start years is one mechanism that can be used so that the analysis better represents the potential costs and benefits of technology application in the rulemaking timeframe.

3. Technology Pathways, Effectiveness, and Cost

Vehicle manufacturers meet increasingly stringent fuel economy standards by applying additional fuel economy-improving technologies to their vehicles. To assess what increases in fuel economy standards could be achievable and at what cost, we first need accurate characterizations of fuel economy-improving technologies. We collected data on over 50 fuel economy-improving technologies that manufacturers could apply to their light-duty (LD) vehicles and heavy-duty pickups and vans (HDPUV) to meet future stringency levels. This includes determining technology effectiveness values, technology costs, and how we realistically expect manufacturers could apply the technologies in the rulemaking timeframe. The characterization of these technologies, the technology effectiveness values, and technology cost assumptions build on work from DOT, EPA, the NAS, and other federal and state government agencies including the Department of Energy's ANL and the California Air Resources Board (CARB).

The light-duty and HDPUV analyses have been conducted in parallel and while their technology pathways, effectiveness, and costs differ, they have been conducted using the same methodology.

After spending over a decade refining the technology pathways, effectiveness, and cost assumptions used in successive CAFE Model analyses, we have developed guiding principles to ensure that the CAFE Model's simulation of manufacturer compliance pathways results in impacts that we would reasonably expect to see in the real world. These guiding principles are as follows:

CAFE Model Files Referenced in this Chapter

Below is a list of CAFE Model Files referenced in this chapter. See Chapter 2.1.9 "Where to Find the Internal NHTSA Files?" for a full list of files referenced in this document and their respective file locations.

- CAFE Model Documentation
- CAFE Model Input File
- Market Data Input File
- Technologies Input File
- CAFE Model Executable File
- CAFE Model Fuel Economy Adjustment Files
- CAFE Analysis Autonomie Documentation
- CAFE Model Battery Costs File
- Vehicle Report Output File
- CAFE Model Compliance Output File
- CAFE Model Program Directory
- Autonomie Input and Assumptions Description File
- BatPaC Lookup Tables

Technologies will have complementary or non-complementary interactions with the full vehicle technology system. The fuel economy improvement from any individual technology must be considered in conjunction with the other fuel economy-improving technologies applied to the vehicle, because technologies added to a vehicle will not result in a simple additive fuel economy improvement from each individual technology. We expect this result in particular from engine and other powertrain technologies that improve fuel economy by allowing the ICE to spend more time operating at efficient engine speed and load conditions, or from engine technologies that both work to reduce the effective displacement of the engine.

***The effectiveness of a technology depends on the type of vehicle the technology is being applied to*.** When we talk about "vehicle type" in our analysis, we're referring to our vehicle technology classes – e.g., a small car, a medium performance SUV, or a pickup truck, among other classes. A small car and a medium performance SUV that use the exact same technology will start with very different fuel economy values; so, when the exact same technology is added to both of those vehicles, the technology will provide a different effectiveness improvement on both of those vehicles.

***The cost and effectiveness values for each technology should be reasonably representative of what can be achieved across the entire industry*.** Each technology model employed in the analysis is designed to be representative of a wide range of specific technology applications used in industry. Some vehicle manufacturers' systems may perform better and cost less than our modeled systems and some may perform worse and cost more. However, employing this approach will ensure that, on balance, the analysis captures a reasonable level of costs and benefits that would result from any manufacturer applying the technology.

***The starting point for cost and effectiveness values must be identified before assuming that a cost or effectiveness value could be employed for any individual technology*.** For example, as discussed below, this analysis uses a set of engine map models that were developed by starting with a small number of initial engine configurations, and then, in a very systematic and controlled process, adding specific well-defined technologies to create a new map for each unique technology combination. Again, providing a consistent reference point to measure incremental technology effectiveness values ensures that we are capturing accurate effectiveness values for each technology combination.

The following subchapters discuss the engine, transmission, electrification, mass reduction, aerodynamic, tire rolling resistance, and other vehicle technologies considered in this analysis. The following subchapters discuss:

- how we define the technology in the CAFE Model,[247]
- how we assign the technology to vehicles in the analysis fleet used as a starting point for this analysis,
- any adoption features applied to the technology, so the analysis better represents manufacturers' real-world decisions,
- the technology effectiveness values, and
- technology cost.

Please note that the following technology effectiveness subchapter provide *examples* of the *range* of effectiveness values that a technology could achieve when applied to the entire vehicle system, in conjunction with the other fuel economy-improving technologies already in use on the vehicle. To see the incremental effectiveness values for any particular vehicle moving from one technology key to a more advanced technology key, see the CAFE Model Fuel Economy Adjustment Files that are installed as part of the CAFE Model Executable File, and not in the input/output folders.

For the light-duty analysis, we show two sets of technology effectiveness charts for each technology type. The charts are titled "Unconstrained" and "Standard Setting." The Standard Setting charts effectiveness values reflect the application of 49 USC 32902 constraints: for example, PHEV technologies only show the effectiveness achieved when operating in a gasoline only mode (charge sustaining mode). The Unconstrained charts show the effectiveness values modeled for the technologies without the 49 USC 32902(h) constraints; for example, PHEV technologies show effectiveness values for their full dual fuel use functionality. The standard setting values are used during the standard setting years being assessed in this analysis, and the unconstrained values are used for all other years modeled.

Similarly, the technology costs provided in each subchapter are *examples* of absolute costs seen in specific model years, for specific vehicle classes. Please refer to the Technologies Input File to see all absolute technology costs used in the analysis across all model years.

3.1. Engine Paths

Internal combustion engines (IC, or ICE) convert chemical energy in fuel to useful mechanical power. The chemical energy is converted to mechanical power by being burned or oxidized inside the engine. The air/fuel mixture entering the engine and burned fuel/exhaust by-products leaving the engine are the working fluids in the engine. The engine power output is a direct result of the work interaction between these fluids and the mechanical components of the engine.[248] The generated mechanical power is used to perform useful work, such as vehicle propulsion.

For this combined analysis, the extensive variety of both light-duty and HDPUV ICE technologies are classified into discrete engine technology paths. These paths are used to model the most representative characteristics, costs, and performance of the fuel economy-improving technologies most likely available during the rulemaking timeframe. The technology paths are intended to represent the range of potential performance levels for each of the technologies. We did not include technologies unlikely to be feasible in the

[247] Note, due to the diversity of definitions industry sometimes employs for technology terms, or in describing the specific application of technology, the terms defined here may differ from how the technology is defined in the industry.
[248] Heywood, J. B. 2018. Internal Combustion Engine Fundamentals. McGraw-Hill Education. Chapter 1.

rulemaking timeframe, technologies unlikely to be compatible with U.S. fuels, or technologies for which there was not appropriate data available to allow the simulation of effectiveness across all vehicle technology classes in this analysis. The technology paths for light-duty and HDPUV can be seen in Figure 3-1 and Figure 3-2 respectively.

Figure 3-1: LD Engine Technology Paths Available

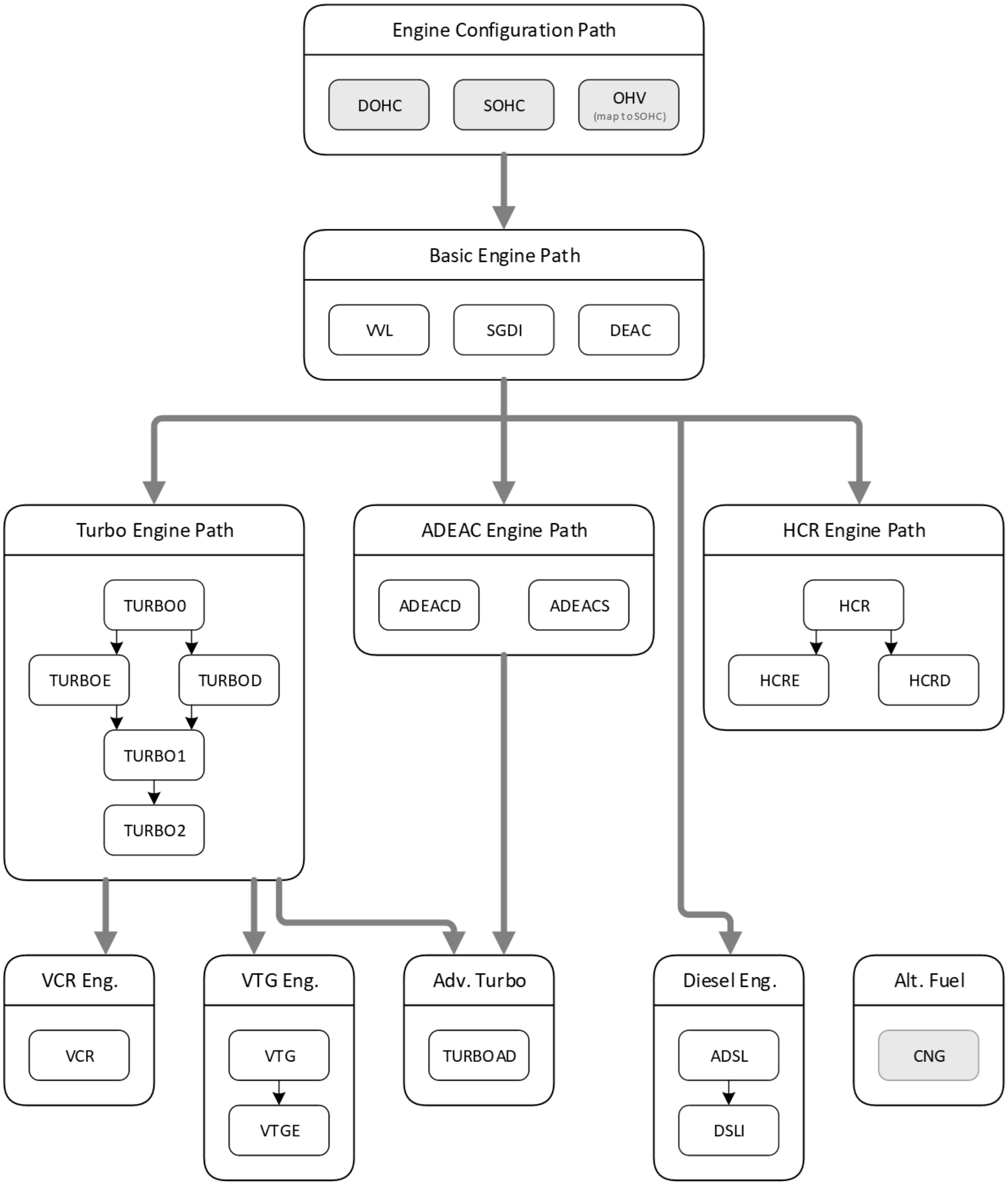
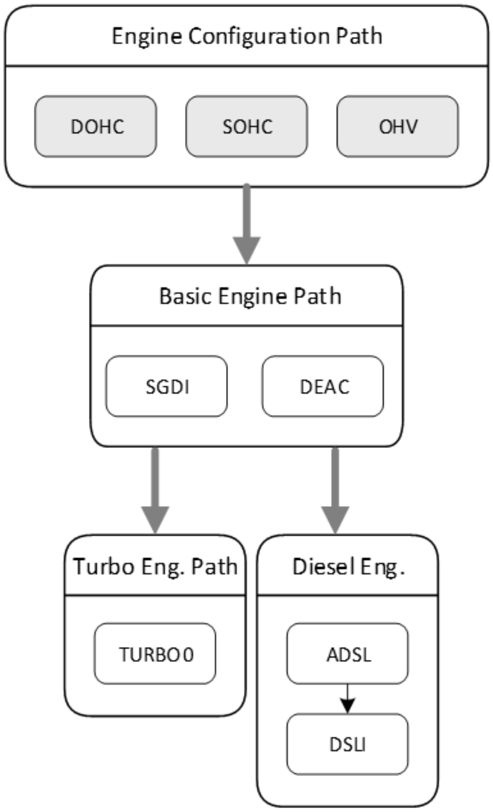


Figure 3-2: HDPUV Engine Technology Paths Available



The following subchapter discusses how we define ICE technologies considered in this analysis. We describe the CAFE Model's general engine technology categories and discuss the engine technologies' relative effectiveness. We also review how the categories are assigned to the model year 2022 light duty analysis fleet and HDPUV analysis fleet, as well as the engine paths' adoption features. Finally, we provide the modeled cost for engine technology application to vehicles.

3.1.1. Engine Technologies

This analysis models ICE technologies manufacturers may use to improve fuel economy for both light-duty vehicles and HDPUVs. Some engine technologies can be incorporated into existing engines with minor or moderate changes to the engines, but many engine technologies require an entirely new engine architecture.

For this analysis we divide engine technologies into two categories, "basic engine technologies" and "advanced engine technologies." "Basic engine technologies" refer to technologies adaptable to an existing engine with minor or moderate changes to the engine. "Advanced engine technologies" refer to technologies that generally require significant changes or an entirely new engine architecture. The words "basic" and "advanced" are not meant to confer any information about the level of sophistication of the technology. Many advanced engine technology definitions also include some basic engine technologies, and these basic technologies are accounted for in the advanced engine's costs and effectiveness values.

The light-duty Engine technology pathways have been selected and refined over a period of more than ten years, based on engines in the market, stakeholder comments, and our engineering judgment – subject to factors listed above, including technologies most likely available during the rulemaking time frame and the range of potential performance levels for each technology, and excluding technologies unlikely to be feasible in the rulemaking timeframe, technologies unlikely to be compatible with U.S. fuels, or technologies for which there was not appropriate data available to allow the simulation of effectiveness across all vehicle technology classes in this analysis.

For technologies in the HDPUV Engine Pathway, we revisited the work done for the HDPUV analysis in the Phase 2 rulemaking and have updated our engine pathway based on that work, the availability of technology in the HDPUV analysis fleet, and technologies we believe will be available in the rulemaking timeframe. The HDPUV fleet is significantly smaller than the light-duty fleet with most vehicles produced by only three manufacturers. These vehicles include work trucks and vans that are focused on transporting people and moving equipment and supplies, and tend to be more focused on a common need than that of the light-duty fleet, which includes sports cars, commuter cars, pickup trucks, grand tourers, etc. As a result of the HDPUV smaller fleet size and narrowed focus, fewer engines and engine technologies are developed or used in this fleet; however, we believe the engines and technologies we have available in the HDPUV analysis fleet and during the rulemaking timeframe are appropriate for this analysis.

3.1.1.1. Basic Engines

In the CAFE Model, basic engine technologies may be applied individually or in combination with other basic engine technologies. The basic engine technologies include variable valve lift (VVL), SGDI, and DEAC. Cylinder deactivation includes a basic level (DEAC) and an advanced level (ADEAC). For this analysis, VVT technology is inherently integrated into all SI basic engines; therefore, it is not a selectable technology and cannot be excluded.

The model applies the basic engine technologies across two engine architectures: dual over-head camshaft (DOHC) engine architecture and single over-head camshaft (SOHC) engine architecture. A third architecture exists, over-head valves (OHV), where the camshaft is not mounted overhead. We mapped engines with this architecture to SOHC engines. Figure 3-3 shows the light-duty basic engine technologies and Figure 3-4 shows the HDPUV basic engine technologies.

Figure 3-3: LD Basic Engine Technologies Path

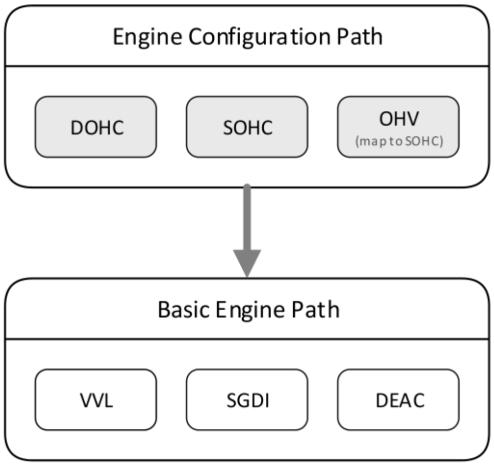
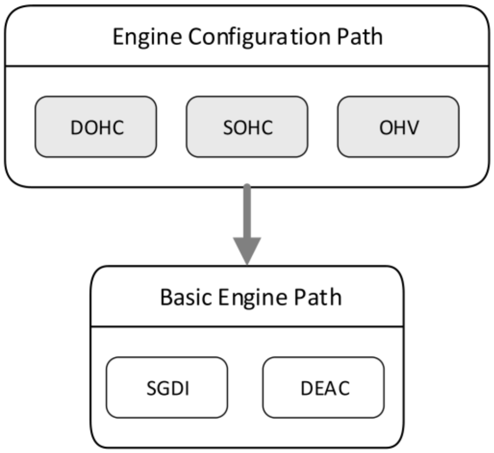


Figure 3-4: HDPUV Basic Engine Technology Path



3.1.1.1.1. Variable Valve Timing

VVT is a family of valve-train designs that dynamically adjusts the timing of the intake valves, exhaust valves, or both, in relation to piston position. VVT can reduce pumping losses, provide increased engine torque and HP over a broad engine operating range, and allow unique operating modes, such as Atkinson cycle operation, to further enhance efficiency.[249] VVT enables more control of in-cylinder air flow for exhaust scavenging and combustion relative to fixed valve timing engines. The basic recycling of exhaust gases using VVT is called internal exhaust gas recirculation (iEGR) and is included as part of the performance improvements provided by the VVT inherent to all engines in this analysis. Engine parameters such as volumetric efficiency, effective compression ratio, and iEGR can all be enabled and accurately controlled by a VVT system. In this analysis VVT is already part of all the DOHC and SOHC engine maps and therefore not a selectable engine technology.

3.1.1.1.2. Variable Valve Lift

VVL dynamically adjusts the distance a valve travels from the valve seat. The dynamic adjustment can optimize airflow over a broad range of engine operating conditions. The technology can increase effectiveness by reducing pumping losses and by affecting the fuel and air mixture motion and combustion in-cylinder.[250] Some manufacturers have implemented a limited, discrete approach to VVL. The discrete approach allows only limited (e.g., two) valve lift profiles versus allowing a continuous range of lift profiles. VVL is still prevalent in the model year 2022 light-duty analysis fleet; however, VVL does not show up in the HDPUV analysis fleet nor is it a selectable technology in the HDPUV analysis. Many of the HDPUV engines use an OHV engine architecture and VVL has not been a technology that has been deployed on these types of engines because of the significant change in engine architecture that would be needed for a relatively small improvement in fuel efficiency. VVL adds a level of cost and complexity that manufacturers have not opted to include in HDPUV engines. For these reasons we do not believe that manufacturers would apply this technology in the HDPUV fleet in the rulemaking timeframe. We do not have any data to support the development of VVL effectiveness technology for HDPUVs for future model years at this time but welcome any information from manufacturers.

3.1.1.1.3. Stoichiometric Gasoline Direct Injection

SGDI sprays fuel at high pressure directly into the combustion chamber, which provides cooling of the in-cylinder charge via in-cylinder fuel vaporization to improve spark knock tolerance and enable an increase in compression ratio and/or more optimal spark timing for improved efficiency.[251] SGDI is common in the light-

[249] 2015 NAS report at 31.
[250] 2015 NAS report, at 32.
[251] 2015 NAS report, at 34.

duty model year 2022 fleet and while this technology is less common in the HDPUV analysis fleet, it is still prevalent. SGDI is not limited to only basic engines; many advanced engines also use the technology.

3.1.1.1.4. Cylinder Deactivation

DEAC disables intake and exhaust valves and turns off fuel injection for the deactivated cylinders during light load operation. DEAC is characterized by a small number of discrete operating configurations.[252] The engine runs temporarily as though it were a smaller engine, reducing pumping losses and improving efficiency. DEAC is present in both the light-duty and HDPUV analysis fleets.

3.1.1.1.5. Camshafts Configuration

For this analysis DOHC engine configurations have two camshafts per cylinder head, one operating the intake valves and one operating the exhaust valves.[253] The basic engine technologies that can be applied to DOHC engines for the light-duty analysis include VVL, SGDI, and DEAC. The HDPUV analysis allows SGDI and DEAC basic engine technologies to be applied to DOHC engines. To represent the possible configurations of basic engine technologies in the analysis, we developed engine fuel map models for each of the technology combinations, as seen in Table 3-1. Each of these engines incrementally adds technology to Eng01, a basic VVT engine with PFI, while holding all other assumptions constant, such as ambient temperature, ambient pressure, base engine geometry, and fuel type. The approach to creating the engine map models is discussed in more detail in Chapter 3.1.4.1.1. DOHC engines are the most common light-duty camshaft configuration of the engine technologies in the model year 2022 analysis fleet, whereas OHV is the most common in the HDPUV fleet.

Table 3-1: Light-Duty DOHC Engine Map Models

Engines	Technologies	Notes
Eng01	DOHC	Parent NA engine, Gasoline, 2.0L, 4 cyl, NA, PFI, DOHC, dual cam VVT, compression ratio (CR) 10.2
Eng02	DOHC+VVL	VVL added to Eng01
Eng03	DOHC+VVL+SGDI	SGDI added to Eng02, CR11
Eng04	DOHC+VVL+SGDI+DEAC	Cylinder deactivation added to Eng03
Eng18	DOHC+SGDI	Gasoline, 2.0L, 4 cyl, NA, SGDI, DOHC, dual cam VVT
Eng19	DOHC+DEAC	Cylinder deactivation added to Eng01
Eng20	DOHC+VVL+DEAC	Cylinder deactivation added to Eng02
Eng21	DOHC+SGDI+DEAC	Cylinder deactivation added to Eng18

SOHC engines are characterized by having a single camshaft in the cylinder head operating both the intake and exhaust valves.[254] The basic engine technologies that can be applied to SOHC engines for the light-duty analysis include VVL, SGDI, and DEAC. The HDPUV analysis allows SGDI and DEAC basic engine technologies to be applied to SOHC engines. Like DOHC engines, engine map models for SOHC engines

[252] 2015 NAS report, at 33.
[253] 2015 NAS report, at 31.
[254] 2015 NAS report, at 31.

use an incremental improvement approach. The SOHC engine map models are based on Eng01 with the removal of one camshaft. We included SOHC VVT Eng5a in previous analyses but did not include it for this analysis. We found that the Eng5a map model's internal friction, inherited from the DOHC engine it was based on, was too high and artificially increased brake-specific fuel consumption (BSFC). As a result of the issue identified with Eng5a, the model applies a valvetrain friction reduction of 0.1 bar over the entire operating range for engine maps 5b, 6a, 7a, and 8a to bring performance of the engines in line with existing data (see Chapter 3.1.4.1.1 for a discussion of engine map validation).[255] SOHC engines are not common in the light-duty model year 2022 analysis fleet but are prevalent in the HDPUV analysis fleet. In both the light-duty and HDPUV analysis, vehicles assigned OHV are mapped to SOHC engines. Table 3-2 shows the light-duty SOHC engine map models and Table 3-3 shows the HDPUV OHV engine map models. Chapter 3.1.4.1.1 discusses how we modeled these configurations. To represent the effectiveness of several other SOHC engine technology combinations, the CAFE Model uses adjustments created from existing related engine map models. Table 3-4 shows the additional SOHC technology combinations with performance values drawn from alternative engine map models.

Table 3-2: Light-Duty SOHC Engine Map Models

Engine	Technologies	Notes
Eng5b	SOHC (valvetrain friction reduction)	Eng5a 2.0L, 4cyl, NA, PFI, single cam VVT with valvetrain friction reduction
Eng6a	SOHC+VVL (valvetrain friction reduction)	Eng02 converted to SOHC with valvetrain friction reduction
Eng7a	SOHC+VVL+SGDI (valvetrain friction reduction)	Eng03 converted to SOHC with valvetrain friction reduction, addition of VVL and SGDI
Eng8a	SOHC+VVL+SGDI+DEAC (valvetrain friction reduction)	Eng04 converted to SOHC with valvetrain friction reduction, addition of DEAC

Table 3-3: HDPUV OHV Engine Map Models

Engines	Technologies	Notes
Eng4a	OHV	7.3L with port fuel injection and 10.5 CR
Eng4b	OHV+SGDI	SGDI and 11.5 CR, naturally aspirated
Eng4c	DOHC+SGDI+DEAC	NA SGDI with DEAC and 11.5 CR

Table 3-4: Light-Duty SOHC Emulated Engines from Analogous Models

Engine Performance is Based on	Technologies	Notes
Eng18	SOHC+SGDI	See Chapter 3.1.4 for effectiveness discussion
Eng19	SOHC+DEAC	See Chapter 3.1.4 for effectiveness discussion
Eng20	SOHC+VVL+DEAC	See Chapter 3.1.4 for effectiveness discussion

[255] Note, the engine friction reduction applied to these engines is not the engine friction reduction technology discussed later in this chapter.

Eng21	SOHC+SGDI+DEAC	See Chapter 3.1.4 for effectiveness discussion

3.1.1.2. Advanced Engines

In the CAFE Model, advanced engine technologies generally refer to families of engine technology that require significant changes in engine structure or an entirely new engine architecture. The advanced engine technologies represent the application of alternate combustion cycles or changes in the application of forced induction to the engine.

Figure 3-5 shows the technology paths for light-duty and Figure 3-6 depicts the technology paths for the HDPUV analyses.

Figure 3-5: The Light-Duty Advanced Engine Technology Paths

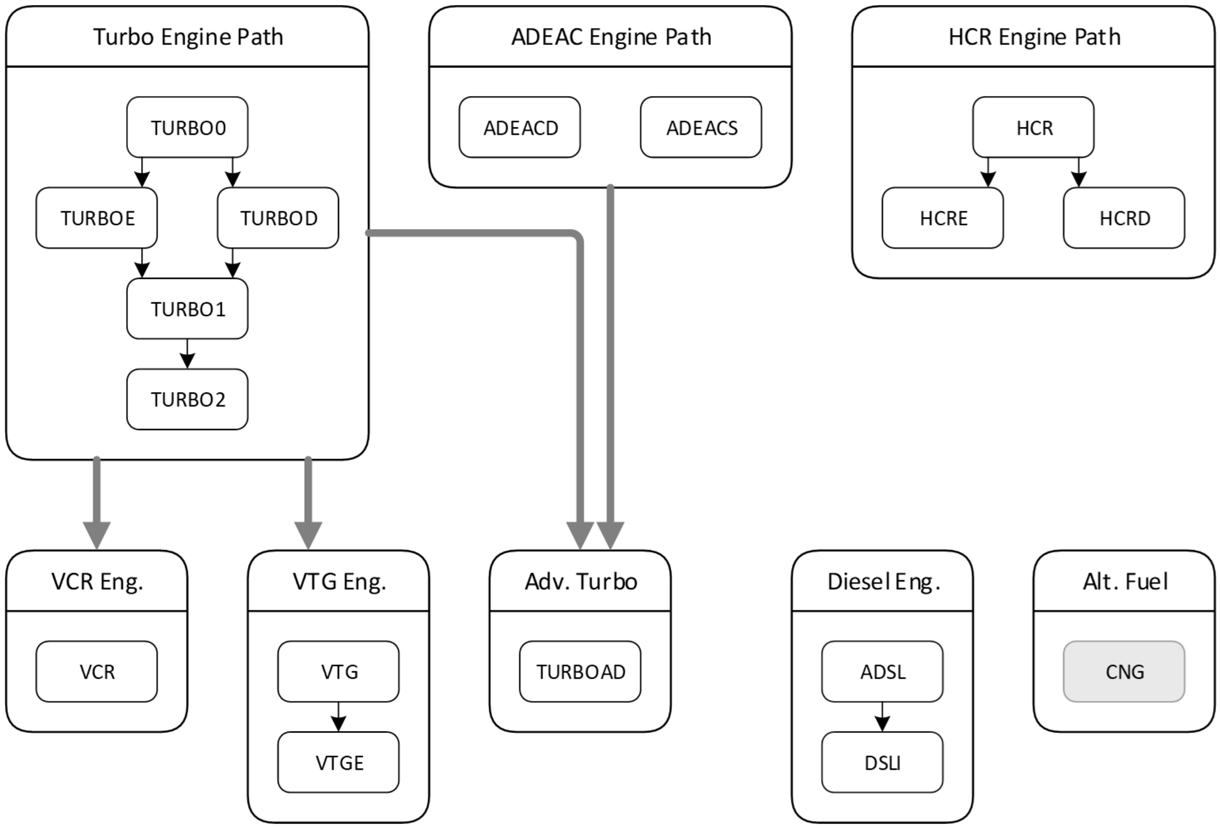
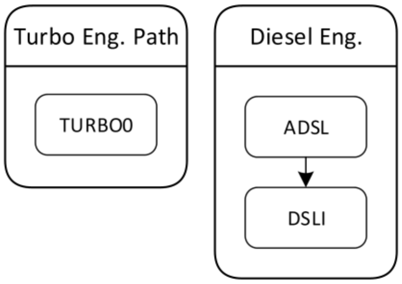


Figure 3-6: The HDPUV Advanced Engine Technology Paths



3.1.1.2.1. Advanced Cylinder Deactivation Engines

ADEAC systems, also known as rolling or advanced DEAC systems, allow a further degree of DEAC than the base DEAC. ADEAC allows the engine to vary the percentage of cylinders deactivated and the sequence in which cylinders are deactivated, essentially providing "displacement on demand" for low load operations. This analysis has two different ADEAC technology paths, an Advanced Cylinder Deactivation with Single Overhead Camshaft (ADEACS), and an Advanced Cylinder Deactivation with Dual Overhead Camshaft (ADEACD). A small number of vehicles have ADEAC technology in the light-duty model year 2022 analysis fleet, though the ADEAC technologies are not part of the HDPUV analysis.

3.1.1.2.2. Forced Induction Engines

Forced induction includes both supercharged and turbocharged downsized engines, which are gasoline SI engines characterized by technology that can create greater-than-atmospheric pressure in the engine intake manifold when higher output is needed. The raised pressure results in an increased amount of airflow into the cylinder supporting combustion, increasing the specific power of the engine. Increased specific power means the engine can generate more power per unit of cylinder volume. The higher power per cylinder volume allows the overall engine volume to be reduced, while maintaining performance. The overall engine volume decrease results in an increase in fuel efficiency by reducing parasitic loads associated with larger engine volumes.[256]

Cooled exhaust gas recirculation (EGR) is also part of the advanced forced induction technology path and is in addition to iEGR discussed earlier. Cooled EGR is another method for diluting the incoming air that takes exhaust gases, passes them through a heat exchanger to reduce their temperature, and then mixes them with incoming air in the intake manifold.[257] Diluting the incoming air with inert exhaust gas reduces pumping losses, improving BSFC. The dilution also reduces combustion rates, temperatures, and pressures, mitigating knock and reducing the need for fuel enrichment. The exhaust gas displaces some incoming air and heats the incoming air, lowering the air's density.

Six levels of turbocharged engine downsizing technologies are considered in this light-duty analysis: turbocharged downsized technology (TURBO0), turbocharged engine with cooled exhausted recirculation (TURBOE), turbocharged engine with DEAC (TURBOD), turbocharged downsized with advanced DEAC (TURBOAD), turbocharged downsized technology (TURBO1), and advanced turbocharged downsized technology (TURBO2). See Table 3-5 for a list of the specific engine map models used to represent the technology levels.

The TURBO0 engine represents a basic level of forced air induction technology being applied to a DOHC-based engine. The TURBO0 engine category assumes application of SGDI to the engine. The engine map model developed to represent the turbocharged downsized engine operates with enough boost pressure to achieve a brake mean effective pressure (BMEP) of less than 24bar. The TURBO0 technology is the only turbo engine available in the HDPUV analysis and while this technology is named the same in both the light-duty and HDPUV analyses, they represent different engines as seen in Table 3-5 and Table 3-6.

Both TURBOE and TURBOD are defined by the application of their respective technologies, cooled EGR and cylinder deactivation, to the TURBO0 engine. The TURBOAD engine is defined by the application of advanced DEAC technology to the TURBO0 engine.

The TURBO1 engine represents a basic level of forced air induction technology being applied to a DOHC-based engine. The TURBO1 engine category assumes application of SGDI and VVL to the engine. The engine map model developed to represent the turbocharged downsized engine operates with enough boost pressure to achieve a BMEP of less than 24bar. The TURBO2 engine category represents an advanced application of forced air induction. The engine map model assumes a DOHC-based engine and application of SGDI and VVL. The engine map model represents performance of an engine boosted to achieve a minimum BMEP of 24bar. A summary of information on light-duty force induction engines is shown in Table 3-5.

The HDPUV analysis uses TURBO0 as the single force induction engine. See Table 3-6 for more information on that engine. We do not see the same turbo technologies and high boost levels in the HDPUV fleet as we

[256] 2015 NAS report, at 34.
[257] 2015 NAS report, at 35.

do in the light-duty fleet, and this is primarily due to the larger engines along with reliability and durability needs of the HDPUV fleet.

Table 3-5: LD Turbocharged Engine Downsizing Technology Engine Map Models

Engine	Technology	Notes
eng36	TURBO0 - 1.6L Turbo DOHC SGDI CR10.5	1.6L, 4 cyl, turbocharged, SGDI, DOHC, VVT
eng37	TURBOE - 1.6L Turbo DOHC SGDI CR10.5 CEGR	Cooled external EGR added to eng36
eng38	TURBOD - 1.6L Turbo DOHC SGDI CR10.5 + DEAC	Cylinder deactivation added to eng36
eng39	TURBOAD - 1.6L Turbo DOHC SGDI CR10.5 + ADEACD	Advanced cylinder deactivation added to eng36
eng12	TURBO1 - DOHC Turbo 1.6L 18bar	1.6L, 4 cyl, turbocharged, SGDI, DOHC, VVT, VVL
eng13	TURBO2 - DOHC Turbo 1.2L 24bar	Eng12 downsized to 1.2L

Table 3-6: HDPUV Turbocharged Engine Downsizing Technology Engine Map Models

Engine	Technology	Notes
eng4d	TURBO0 - Turbo OHV SGDI CR9.5	Turbocharged downsized with SGDI 4V, independent cam phaser (VVT)

3.1.1.2.3. High Compression Ratio and Atkinson Engines

In this analysis, high compression ratio (HCR) engines represent a class of SI engines that achieve a higher level of fuel efficiency by implementing a high geometric compression ratio with varying degrees of late intake valve closing (LIVC) and without the use of an electric drive motor.[258,259] These engines operate on a modified Atkinson cycle allowing for improved fuel efficiency under certain conditions but still offering enough power to not require an electric machine (EM); however, there are limitations on how HCR engines can apply the modified Atkinson cycle and the types of vehicles that can use this technology (see Chapter 3.1.1.2.3.1 and Chapter 3.1.3.3). In this analysis, the Atkinson engine also achieves a higher level of fuel efficiency using a full-time Atkinson cycle engine and an electric drive motor. The full time Atkinson engine in this analysis is only used in HEVs (see Chapter 3.1.1.2.3.2).

Historically, the Otto combustion cycle has been used by most gasoline-based SI engines.[260] Increased research into improving fuel economy has resulted in the development of alternate combustion cycles that allow for greater levels of thermal efficiency. One such alternative combustion cycle is the Atkinson cycle. Modern Atkinson cycle engines use LIVC to create a greater expansion ratio than the effective compression

[258] Late intake valve closing (LIVC) is a method manufacturers use to reduce the effective compression ratio and allow the expansion ratio to be greater than the compression ratio resulting in improved fuel economy but reduced power density.
[259] See the 2015 NAS report, Appendix D, for a short discussion on thermodynamic engine cycles.
[260] Otto cycle is a four-stroke cycle that has four piston movements over two engine revolutions for each cycle. First stroke: intake or induction; seconds stroke: compression; third stroke: expansion or power stroke; and finally, fourth stroke: exhaust.

ratio, thereby maximizing efficiency and use an electric machine to supplement the loss in power density.[261,262] The main principles behind the Atkinson cycle are over-expansion of the combustion gasses and reduced pumping losses. The gasses in the expansion stroke are allowed to expand until the pressure in the cylinder is the same as the ambient pressure outside of the cylinder. This over-expansion of the combustion gasses allows more work to be extracted from the combustion process resulting in improved fuel efficiency.[263,264]

Currently, there are two common approaches to achieving Atkinson Cycle operation: either the exhaust valve timing is modified, or the intake valve timing is modified. If the exhaust valve timing is modified, the exhaust valve will not open until enough expansion has occurred for the cylinder pressure to be as close to atmospheric pressure as the cylinder geometry allows. If the intake valve timing is modified, the intake valve will stay open during some portion of the compression stroke. When the intake valve stays open, some of the fresh charge is driven back into the intake manifold by the rising piston so the cylinder is never filled completely with fresh air, effectively creating a longer expansion stroke than compression stroke and reducing pumping losses.[265] It is important to note that in both cases, the geometric compression ratio of the engine will be different (higher) than the actual, or effective, compression ratio of the engine.[266,267]

One major disadvantage of the Atkinson cycle is a significant reduction in power density.[268,269] The reduced power density is a result of the decreased amount of air in the cylinder at the moment of combustion compared to the total volume of the cylinder. The trade-off in power density for thermal efficiency generally relegates these engines to lower power applications, such as in parallel with an electric powertrain, like in the Toyota Prius, or in conjunction with road load reducing technologies that reduce the need for engine power to maintain vehicle performance.[270,271]

Descriptions of HCR engines and Atkinson cycle engine technologies have been used interchangeably in association with HCR engines for previous rulemaking analyses. Both technologies achieve a higher thermal efficiency than traditional Otto cycle engines, however, the two engine types operate differently. For purposes of this analysis, HCR and Atkinson technologies are categorized into two groups: (1) HCR engines and (2) Atkinson engines.

3.1.1.2.3.1. High Compression Ratio Engines

For this analysis we define HCR engines as being naturally aspirated, gasoline, spark ignition, using a geometric compression ratio of 12.5:1 or greater,[272] and able to dynamically apply various levels of LIVC based on load demand. An HCR engine uses less fuel for each engine cycle, which increases fuel economy, but decreases power density (or torque). Generally, during high loads – when more power is needed – the engine will use variable valve actuation to reduce the level of LIVC by closing the intake valve earlier in the compression stroke (leaving more fuel in the compression chamber), increasing the effective compression ratio, reducing over-expansion, and sacrificing efficiency for increased power density.[273] However, there is a limit to how much air-fuel mixture can remain in the compression chamber of an HCR engine because over-

261 Yamaji, K. et al. 2018. New 2.0L I4 Gasoline Direct Injection Engine with Toyota New Global Architecture Concept. SAE Technical Paper 2018-01-0370. Available at: https://www.sae.org/publications/technical-papers/content/2018-01-0370/. (Accessed: Feb. 8, 2024).

262 Feng, R. et al. 2016. Investigations of Atkinson Cycle Converted from Conventional Otto Cycle Gasoline Engine. SAE Technical Paper 2016-01-0680. Available at: https://www.sae.org/publications/technical-papers/content/2016-01-0680/. (Accessed: Feb. 8, 2024).

263 Compression ratio is the ratio of the maximum to minimum volume in the cylinder of an internal combustion engine.

264 Expansion ratio is the ratio of maximum to minimum volume in the cylinder of an ICE when the valves are closed (i.e., the piston is traveling from top to bottom to produce work).

265 Heywood, J.B. 2018. Internal Combustion Engine Fundamentals. McGraw-Hill Education. Chapter 5.

266 Geometric compression ratio is the ratio of the maximum volume when a cylinder is at full expansion versus the minimum volume in a cylinder at full compression.

267 Effective compression ratio is the difference in volume in a cylinder when the volume of gas is held constant to the volume in a cylinder at full compression.

268 Power density is the engine power per unit of displacement (= [Engine Power]/[Engine Displacement]).

269 Heywood, J.B. 2018. Internal Combustion Engine Fundamentals. McGraw-Hill Education. Chapter 5.

270 Toyota. 2015. Under the Hood of the All-new Toyota Prius. Last revised: Oct. 13, 2015. Available at: https://global.toyota/en/detail/9827044. (Accessed: Feb. 8, 2024).

271 Road load reducing technologies include rolling resistance reduction technologies, vehicle MR and aerodynamic drag reduction.

272 Note that even if an engine has a compression ratio of 12.5:1 or greater does not necessarily mean it is an HCR engine in our analysis; as discussed in the section on engine assignements below, we look at a number of factors to perform baseline engine assignments.

273 Variable valve actuation is a general term used to describe any single or combination of VVT, VVL, and Variable Valve Duration used to dynamically alter an engines valvetrain during operation.

compression of the air-fuel mixture can lead to engine knock. Conversely, at low loads the engine will typically increase the level of LIVC by closing the intake valve later in the compression stroke, reducing the effective compression ratio, increasing the over-expansion, and sacrificing power density for improved efficiency. By closing the intake valve later in the compression stroke (i.e., applying more LIVC) the engine's displacement is effectively reduced, which results in less air and fuel for combustion and a lower power output. This modified Atkinson cycle can be used to mitigate, but not eliminate, the low power density issues that can constrain the application of a full time Atkinson cycle engine.

When we say, "lower power density issues," this translates to a low torque density,[274] meaning that the engine cannot create the torque required at necessary speeds to meet load demands. To the extent that a vehicle requires more power in a given condition than an engine with low power density can provide, that engine would experience issues like engine knock for the reasons discussed above; but more importantly, an engine designer would not allow an engine application where the engine has the potential to operate in unsafe conditions in the first place. Instead, a manufacturer could significantly increase an engine's displacement (i.e., size) to overcome those low power density issues (which would decrease the vehicle's fuel economy),[275] add an electric motor and battery pack to provide the engine with more power or (most likely) apply a different type of engine technology altogether, like a downsized, turbocharged engine.[276]

Vehicle manufacturers' intended performance attributes for a vehicle – like payload and towing capability, intention for off-road use, and other attributes that affect frontal area and rolling resistance – dictate whether an HCR engine can be a suitable technology choice for that vehicle.[277,278] As vehicles require higher payloads and towing capacities,[279] or experience road load increases from larger all-terrain tires or a larger frontal area and less aerodynamic design, or experience driveline losses for AWD and 4WD configurations, more engine torque is required at all engine speeds. Any time more engine torque is required the application of this technology becomes less effective and more limited.[280] For these reasons, to maintain a performance-neutral analysis, and as discussed further below, we limit non-hybrid and non-plug-in-hybrid HCR engine application to certain categories of vehicles.[281] Also for these reasons, HCR engines are not found in the HDPUV analysis fleet, nor are they available as an engine option in the HDPUV analysis.

Three HCR engines are available in the light-duty analysis: (1) the basic level Atkinson-enabled engine (HCR) with VVT and SGDI, (2) the Atkinson enabled engine (HCRE) with cooled exhaust gas recirculation (CEGR), and finally, (3) the Atkinson enabled engine with DEAC (HCRD). A summary of each of the engine technologies is shown in Table 3-7. Note that these three engines are also available to be paired with P2 technologies in the Hybridization Paths Collection – the hybrid versions of these engines and their adoption features are discussed in Chapter 3.3.

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[274] Torque = radius x force.

[275] But see the 2023 EPA Trends Report at 48 ("As vehicles have moved towards engines with a lower number of cylinders, the total engine size, or displacement, is also at an all-time low."), and the discussion below about why we do not believe manufacturers will increase the displacement of HCR engines to make the necessary power.

[276] See, e.g., Toyota. 2023. 2024 Toyota Tacoma Makes Debut on the Big Island, Hawaii. Available at: https://pressroom.toyota.com/2024-toyota-tacoma-makes-debut-on-the-big-island-hawaii/. (Accessed: Feb. 8, 2024).

[277] Supplemental Comments of Toyota Motor North America, Inc., Notice of Proposed Rulemaking: Safer Affordable Fuel-Efficient Vehicles Rule, Docket ID Numbers: NHTSA-2018-0067 and EPA-HQ-OAR-2018-0283. at 6.

[278] Feng, R. et al. 2016. Investigations of Atkinson Cycle Converted from Conventional Otto Cycle Gasoline Engine. SAE Technical Paper. Available at: https://www.sae.org/publications/technical-papers/content/2016-01-0680/. (Accessed: Feb. 8, 2024).

[279] See Tucker, S. 2023. What Is Payload: A Complete Guide. Kelly Blue Book. Last revised: Feb. 2, 2023. Availale at: https://www.kbb.com/car-advice/payload-guide/#link3. (Accessed: Feb. 8, 2024). ("Roughly speaking, payload capacity is the amount of weight a vehicle can carry, and towing capacity is the amount of weight it can pull. Automakers often refer to carrying weight in the bed of a truck as hauling to distinguish it from carrying weight in a trailer or towing.").

[280] Supplemental Comments of Toyota Motor North America, Inc., Notice of Proposed Rulemaking: Safer Affordable Fuel-Efficient Vehicles Rule, Docket ID Numbers: NHTSA-2018-0067 and EPA-HQ-OAR-2018-0283. ("Tacoma has a greater coefficient of drag from a larger frontal area, greater tire rolling resistance from larger tires with a more aggressive tread, and higher driveline losses from 4WD. Similarly, the towing, payload, and off road capability of pick-up trucks necessitate greater emphasis on engine torque and horsepower over fuel economy. This translates into engine specifications such as a larger displacement and a higher stroke-to-bore ratio…. Tacoma's higher road load and more severe utility requirements push engine operation more frequently to the less efficient regions of the engine map and limit the level of Atkinson operation…This endeavor is not a simple substitution where the performance of a shared technology is universal. Consideration of specific vehicle requirements during the vehicle design and engineering process determine the best applicable powertrain.").

[281] To maintain performance neutrality when sizing powertrains and selecting technologies we perform a series of simulations in Autonomie which are further discussed in the Chapter 2.3.4 and in the CAFE Analysis Autonomie Documentation. The concept of performance neutrality is discussed in detail in Section II.C.3 (titled "Technology Effectiveness Values") of the final rule preamble, and additional reasons why we maintain a performance neutral analysis are discussed in Section II.C.6 (titled "Technology Applicability Equations and Rules") of the final rule preamble.

Table 3-7: LD Atkinson Enabled Engine Map Models

Engine	Technology	Notes
eng32	HCR - 2.5L NA, DOHC CR13 SGDI	2.5L, NA, high compression ratio, VVT, SGDI
eng33	HCRE - 2.5L NA DOHC CR13 SGDI CEGR	Cooled external EGR added to eng32
eng34	HCRD - 2.5L NA DOHC CR13 SGDI + DEAC	Cylinder deactivation added to eng32

3.1.1.2.3.2. Atkinson Engines - Hybrid Electric Vehicle Engines

Atkinson engines operate in a full time Atkinson cycle that incorporates the use of an EM to assist in vehicle propulsion. The most common method of achieving Atkinson operation is the use of late intake valve closing. This method allows backflow from the combustion chamber into the intake manifold, reducing the effective compression ratio, and providing a higher expansion ratio. The higher expansion ratio improves thermal efficiency but reduces power density. The low power density generally relegates these engines to hybrid vehicle applications only. Coupling the engines to EMs and significantly reducing road loads can compensate for the lower power density and maintain desired performance levels for the vehicle.[282] The Toyota Prius is an example of a vehicle that uses an Atkinson engine. The 2017 Toyota Prius achieved a peak thermal efficiency of 40 percent.[283]

Table 3-8: Atkinson Engine Map Model

Engine	Technology	Notes
Eng26	SHEVPS PHEV20PS PHEV50PS	HEV-PHEV Atkinson Cycle Engine 1.8L

The Atkinson engine in our analysis, Eng26, is used for “power split” hybrid vehicle architectures. We also model “parallel”, or P2, architectures for SHEVs and PHEVs. We allow P2 hybrids to be paired with conventional basic engines, HCR engines, and TURBO0 engines. For more discussion on these different configurations see Chapter 3.3.1.4.

3.1.1.2.4. Miller Cycle Engines

The Miller cycle is another type of overexpansion combustion cycle similar to the Atkinson cycle. The Miller cycle, however, operates in combination with a forced induction system that helps address the impacts of reduced power density during high load operating conditions. Miller cycle-enabled engines use a similar technology approach as seen in Atkinson-enabled engines to effectively create an extended expansion stroke of the combustion cycle.

Miller cycle-enabled engines have a similar trade-off in power density as Atkinson engines; the lower power density requires a larger volume engine in comparison to an Otto cycle-based turbocharged system for similar applications.[284] However, the forced air induction does mitigate power density issues, and allows for a wider application of the engine technology. Miller cycle-enabled engines may use a variable geometry turbocharger

[282] Toyota. 2015. Under the Hood of the All-new Toyota Prius. Last revised: Oct. 13, 2015. Available at: https://global.toyota/en/detail/9827044. (Accessed: Feb. 8, 2024).
[283] Matsuo, S. et al. 2016. The new Toyota Inline 4 Cylinder 1.8L ESTEC 2ZR-FXE Gasoline Engine for Hybrid Car. SAE Technical Paper 2016-01-0684. Available at: https://doi.org/10.4271/2016-01-0684. (Accessed: Feb. 8, 2024).
[284] 2021 NAS report at Section 4.

to increase engine power density over a broader range of operating conditions and increase the amount of Miller cycle operation. The application of an electronic assist or electronic boost system may further mitigate the power density reduction, particularly at low-speed operating conditions.

We use two engine map models to represent Miller cycle-enabled engines, see Table 3-9. These advanced engines can only be applied in the light-duty analysis and are not part of the HDPUV technology path. The basic level Miller cycle-enabled engine includes the application of a variable turbo geometry technology (VTG). The advanced Miller cycle-enabled system includes the application of at least a 40V-based electronic boost system (VTGE). VTG technology allows the system to vary boost level based on engine operational needs. The use of a variable geometry turbocharger also supports the use of cooled exhaust gas recirculation.[285]

An electronic boost system has an electric motor added to assist a turbocharger at low engine speeds, mitigating turbocharger lag and providing extra boost needed to overcome the torque deficit at low engine speeds and loads.[286]

Table 3-9: Miller Cycle Engine Map Models

Engine	Technology	Notes
eng23b	VTG - Miller+SGDI	2.0L, 4 cyl, CR12, Miller Cycle turbo, SGDI, DOHC, CEGR. VVT, VVL with VTG
eng23c	VTGe - Miller eCharger+SGDI	2.0L, 4 cyl, CR12, Miller Cycle turbo SGDI, DOHC, VVT, CEGR, eCharger

3.1.1.2.5. Variable Compression Ratio Engines

Variable compression ratio (VCR) engines work by changing the length of the piston stroke of the engine to optimize the compression ratio and improve thermal efficiency over the full range of engine operating conditions. Engines that use VCR technology are currently in production as small displacement turbocharged in-line four-cylinder, high BMEP (23-27 bar) applications. Nissan is the only manufacturer to use this technology in the model year 2022 analysis fleet.

One engine map model represents a VCR system. See Table 3-10 for more information on the VCR technology.

Table 3-10: Variable Compression Ratio Engine Map Model

Engine	Technology	Notes
eng26a	VCR - SGDI+Turbo	Gasoline, 2.0L, 4 Cylinder, CR9/12, SGDI, Variable Compression Ratio, with CEGR, VVT, turbocharged

3.1.1.2.6. Diesel Engines

Diesel engines have several characteristics that result in better fuel efficiency over traditional gasoline engines, including reduced pumping losses due to lack of (or greatly reduced) throttling, high pressure direct injection of fuel, a combustion cycle that operates at a higher compression ratio,[287] and a very lean air/fuel

[285] 2015 NAS report, at 116.
[286] 2015 NAS report, at 62.
[287] The diesel cycle is also a four-stroke cycle like the Otto Cycle, except in the intake stroke no fuel is injected and fuel is injected late in the compression stroke at higher pressure and temperature.

mixture relative to an equivalent-performance gasoline engine.[288] However, diesel technologies require additional enablers, such as a NO_X adsorption catalyst system or a urea/ammonia selective catalytic reduction system, for control of NO_X emissions.

We considered two levels of diesel engine technology for the light-duty fleet (see Table 3-11). The basic level diesel engine technology (ADSL) is new for this analysis and based off a modern 3.0L turbocharged diesel engine. We developed a more advanced diesel engine (DSLI) by adding DEAC to the ADSL engine technology. The light-duty analysis and the heavy-duty vans within the HDPUV analysis base the ADSL and advanced diesel engine with improvements (DSLI) technologies off the same engine; however, the heavy-duty pickups within the HDPUV analysis based the ADSL and DSLI technologies off a larger 6.7L diesel engine, see Table 3-12. This is discussed further in Chapter 3.1.4.1.1.

Table 3-11: LD Diesel Engine Map Models

Engine	Technology	Notes
eng45	ADSL - 3.0L Diesel	Modern turbocharged 3.0L Diesel
eng46	DSLI - 3.0L Diesel + DEAC	Cylinder deactivation added to eng45

Table 3-12: HDPUV Diesel Engine Map Models

Engine	Technology	Notes
eng3a	ADSL - Diesel basic level for Van	Modern turbocharged 3.0L Diesel
eng3c	DSLI - Diesel basic level + cylinder deactivation for Van	Cylinder deactivation added to eng3c
eng1a	ADSL - Diesel basic level for HD Pickup	Modern turbocharged 6.7L Diesel
eng1c	DSLI - Diesel basic level + cylinder deactivation for HD Pickup	Eng1c with Cylinder Deactivation

3.1.1.2.7. Alternative Fuel Engines

Compressed natural gas (CNG) systems are ICEs that run on natural gas as a fuel source. The fuel storage and supply systems for these engines differ tremendously from gasoline, diesel, and flex fuel vehicles.[289] CNG engines are a basic level-only technology and are not applied to any vehicle that did not already include a CNG engine. The model year 2022 light-duty and HDPUV analysis fleets do not include any dedicated CNG vehicles.

[288] See the 2015 NAS report, Appendix D, for a short discussion on thermodynamic engine cycles.
[289] Flexible fuel vehicles (FLEX) are designed to run on gasoline or gasoline-ethanol blends of up to 85 percent ethanol.

3.1.2. Assigning Engine Technologies in the Analysis Fleet

Manufacturers have steadily improved the fuel economy of their vehicles through implementation of greater levels of fuel economy-improving technology in their fleets.[290] We built two analysis fleets to best capture the current level of these advances and update the market data inputs for the CAFE Model. We built the light-duty fleet using mid-model year 2022 CAFE compliance data, press releases, vehicle benchmarking studies, technical publications, and CBI. We use these sources to ensure the fleet is represented as accurately as possible. We built the HDPUV fleet using compliance data along with press releases, vehicle benchmarking studies, technical publications, and CBI. For further discussion see Chapter 2.2.

We use data for each manufacturer to determine which platforms share engines. Within each manufacturer's fleet, we assign unique identification designations (engine codes) based on configuration, technologies applied, displacement, compression ratio, and power output. We use power output to distinguish between engines that might have the same displacement and configuration but significantly different HP ratings.

While we treat engine assignments the same in the light-duty and HDPUV analyses, engine codes are not shared between the two fleets, and engine technologies are not shared between the fleets, with one exception.[291] The different engine maps for the light-duty and HDPUV analysis are discussed in Chapter 3.1.4.1.1. This is done because the engines between these two fleets are different in the real world and different in this analysis. HDPUVs are work vehicles and their engines must be able to handle additional work such as higher payloads, towing, and additional stop and go demands. This results in HDPUVs often requiring larger, more robust, and more powerful engines. See the HDPUV and LD Market Data Input Files for a further understanding of how the engine sizes and power differ between the HDPUV and LD fleets.

The CAFE Model identifies leaders and followers for a manufacturer's vehicles that use the same engine, indicated by sharing the same engine code. The model automatically determines which engines are leaders by using the highest sales volume row of the highest sales volume nameplate that is assigned an engine code. This leader-follower relationship allows the CAFE Model simulation to maintain engine sharing as more technology is applied to engines.

As an example, the 2022 Chevrolet Silverado has four different engine displacements available. The engines include a 2.7L turbocharged I4, a 5.3L naturally aspirated V8, a 6.2L naturally aspirated V8, and a 3.0L turbo diesel I6. As discussed above, we assign each engine one unique engine code or assign one engine multiple codes if there are variants that use different technologies. For example, we assign the 2022 Chevrolet Silverado naturally-aspirated 5.3L V8 engine one of two engine codes: 115301 (gasoline only with cylinder deactivation), and 115302 (gasoline only with advanced cylinder deactivation).[292] All Silverados that use one of these engines will reference the same engine code. We then assign the appropriate corresponding technology to each engine code, and the model can accurately account for further engine improvements at each vehicle redesign and propagate them to each vehicle model that uses the engine code.

We accurately represent each engine using engine technologies and engine technology classes. We assign each engine code technology that most closely corresponds to an engine map, as discussed in Chapter 3.1.4.1.1. For most technologies, one box on the technology tree corresponds to one engine map that corresponds to one engine code. Basic engine technologies, which may be applied individually or in combination with other basic engine technologies, are represented by a suite of engine maps, depending on the basic technologies that are combined, as shown in Table 3-1. Some technologies are represented by the same engine map, as is the case with "eng26" being used for SHEVPS, PHEV20PS, and PHEV50PS. This can be seen through Table 3-1 to Table 3-12 above, where one engine map (with the prefix signifier "eng") is directly related to one or more technologies (e.g., the HDPUV diesel engine map model "eng3a" relates to the ADSL box on the HDPUV technology tree).

[290] EPA. 2023. The 2023 Greenhouse Gas Emissions, Fuel Economy, and Technology since 1975. The 2023 EPA Automotive Trends Final Report. EPA-420-R-22-033. Washington, D.C. at 1-15. Available at: https://www.epa.gov/system/files/documents/2023-12/420s23002.pdf. (Accessed: Feb. 22, 2024) (hereinafter, 2023 EPA Automotive Trends Report).
[291] The light-duty diesel engine technology ADSL and DSLI are shared with the heavy-duty vans. light-duty diesel engines have high towing and payload capabilities for their class that are similar to the heavy-duty vans.
[292] Market Data Input File, 'Vehicles' Tab, Line 235, 281, Column I.

When we assign engine technologies in the analysis fleet, we must look at the *actual* technologies on a manufacturer's engine and compare those technologies to the engine technologies (remember, specific boxes on the technology tree, represented by a specific engine map) *in our analysis*. We have just over 270 unique engine codes in the light-duty analysis fleet and just over 20 unique engine codes in the HDPUV fleet, meaning that for both analysis fleets, our engineers identify the technologies present on those almost 300 unique engines in the real world, and make decisions about which of our approximately 40 engine map models (and therefore engine technology on the technology tree) best represent those real-world engines.

When we are looking at how to best fit each of those 300 engines to our 40 engine technologies/engine maps, we use specific technical elements contained in manufacturer publications, press releases, vehicle benchmarking studies, technical publications, manufacturer's specification sheets, and occasionally CBI (like the specific technologies, displacement, compression ratio, and power mentioned above), and engineering judgment. For example, in the light-duty analysis, an engine with a 13.0:1 compression ratio is a good indication that an engine would be considered an HCR engine in our analysis, and some engines that achieve a slightly lower CR, e.g., 12.5, may be considered an HCR engine depending on other technology on the engine, like inclusion of SGDI, increased engine displacement compared to other competitors, high energy spark system, and/or reduction of engine parasitic losses through variable or electric oil and water pumps.

Most engines that have technologies like turbocharging and DEAC are less complicated to assign to our engine maps, but more complex engines need data and engineering judgment to be assigned. However, we believe that our engine mapping captures the fuel-efficient technologies manufacturers have deployed for model year 2022 and in the HDPUV fleet.

We assign each individual vehicle's initial fuel economy value based on CAFE or FE compliance data for that vehicle, and not based on these maps. Then, the compliance modeling uses these engine maps to determine a percent efficiency gain from the application of a new technology applied to that base level value for each individual vehicle, see Chapter 3.1.4.

The engine technology classes are a second identifier used in the analysis to accurately account for engine costs. The engine technology class is formatted as number of cylinders followed by the letter C, number of banks followed by the letter B, and an engine head configuration designator, which is _SOHC for single overhead cam, _ohv for overhead valve, or blank for dual overhead cam. Table 3-13 and Table 3-14 show examples of observed engines with their corresponding assigned engine technologies as well as engine technology classes for the light-duty and HDPUV fleets.

Table 3-13: Examples of Observed Engines and Their Corresponding Engine Technology Class and Technology Assignments in the LD Fleet

Vehicle	Engine Observed	Engine Technology Class Assigned	Engine Technology Assigned
GMC Acadia	Naturally Aspirated DOHC V6	6C2B	SGDI
VW Arteon	Turbocharged DOHC I4	6C2B	TURBO2
Bentley Bentayga	Turbocharged DOHC W12 w/ cylinder deactivation	16C4B	TURBOD
Honda Passport	Naturally Aspirated SOHC V6	6C2B_SOHC	VVL, SGDI, DEAC
Honda Civic	Turbocharged DOHC I4	4C1B	TURBO1
Cadillac CT5	Turbocharged DOHC V6 w/ cylinder deactivation	8C2B	TURBOD

Ford Escape	Turbocharged DOHC I3	4C1B_L	TURBOD
Chevrolet Silverado	Naturally Aspirated OHV V8 w/ skip fire	8C2B_ohv	ADEACS

Table 3-14: Examples of Observed Engines and Their Corresponding Engine Technology Class and Technology Assignments in the HDPUV Fleet

Vehicle	Engine Observed	Engine Technology Class Assigned	Engine Technology Assigned
Ram 3500 Pickup	Turbocharged I6 Diesel	6C1B_ohv_2b3	ADSL
Ram 2500 Pickup	Naturally Aspirated OHV V8 w/ cylinder deactivation	8C2B_ohv_2b3	SGDI, DEAC
Ford T350 Extended Passenger Wagon	Turbocharged DOHC V6 w/ cylinder deactivation	8C2B_2b3	TURBO0
Ford T150 Cargo Van	Naturally Aspirated DOHC V6	6C2B_2b3	DOHC

As discussed in the engine cost subchapter (see Chapter 3.1.5) the cost tables for a given engine class include downsizing (to an engine architecture with fewer cylinders) when turbocharging technology is applied; therefore, the turbocharged engines observed in the model year 2022 analysis fleet (that have already been downsized) often map to an engine class with more cylinders. For instance, an observed TURBO1 V6 engine would map to an 8C2B (V8) engine class, because the turbo costs on the 8C2B engine class tab assume a V6 (6C2B) engine architecture. Similarly, as indicated above, the TURBO1 I3 in the Ford Escape maps to the 4C1B_L (I4) engine class, because the turbo costs on the 4C1B_L engine class tab assume a I3 (3C1B) engine architecture. Some instances can be more complex, including low HP variants for 4cylinder engines, and are shown in Table 3-15. Diesel engines map to engine technology classes that match the observed cylinder count since naturally aspirated diesel engines are not found in new light-duty vehicles in the U.S. market. Table 3-16 and Table 3-17 includes the full list of engine classes included in the CAFE Model analysis and the corresponding cylinder count that would be observed on engines included in that class.

Table 3-15: LD and HDPUV Engine Technology Class Assignment Logic

Observed Gasoline Engine Architecture	Observed Number of Cylinders	Horsepower	Naturally Aspirated or Turbo	Engine Technology Class Assigned
Inline	3	Any	NA	3C1B
Inline	3	Any	Turbo	4C1B_L
Inline	4	<=180	NA	4C1B_L
Inline	4	<=180	Turbo	4C1B
Boxer	4	<=180	NA	4C2B_L
Boxer	4	<=180	Turbo	4C2B
Inline	4	>180	NA	4C1B
Inline	4	>180	Turbo	6C2B
Boxer	4	>180	Turbo	6C2B
Inline	5	Any	Turbo	6C2B
W (LD Only)	16	Any	Turbo	16C4B

Table 3-16: LD Observed Cylinder Count by Engine Technology Class and Engine Technology

Broad Engine Technology Category	Basic Engine	Turbocharged	Advanced Naturally Aspirated	Diesel
Included Technologies	**VVL, SGDI, DEAC**	**TURBO0, TURBOE, TURBOD, TURBO1, TURBOAD, TURBO2, VCR, VTG, VTGE**	**ADEACS, ADEACD, HCR, HCRE, HCRD**	**ADSL, DSLI**
2C1B_SOHC	2	2	2	2
2C1B	2	-	2	2
3C1B_SOHC	3	-	3	3
3C1B	3	-	3	3
4C1B_L_SOHC	4	3	4	4
4C1B_SOHC	4	4	4	4
4C1B_L	4	3	4	4
4C1B	4	4	4	4
4C2B_SOHC	4	4	4	4
4C2B_L	4	3	4	4
4C2B	4	4	4	4
5C1B_SOHC	5	-	5	5
5C1B	5	-	5	5
6C1B_SOHC	6	-	6	6
6C1B	6	-	6	6
6C1B_ohv	6	-	6	6
6C2B_SOHC	6	-	6	6
6C2B	6	4 or 5	6	6
6C2B_ohv	6	-	6	6
8C2B_SOHC	8	-	8	8
8C2B	8	6	8	8
8C2B_ohv	8	-	8	8
10C2B_SOHC	10	-	10	10
10C2B	10	8	10	10
10C2B_ohv	10	-	10	10
12C2B_SOHC	12	-	12	12
12C2B	12	10	12	12
12C4B_SOHC	12	-	12	12
12C4B	12	10	12	12
16C4B_SOHC	16	-	16	16
16C4B	16	12 or 16	16	16

Table 3-17: HDPUV Observed Cylinder Count by Engine Technology Class and Engine Technology

Broad Engine Technology Category	Basic Engine	Turbocharged	Diesel
Included Technologies	**SGDI, DEAC**	**TURBO0**	**ADSL, DSLI**
4C1B	4	4	4
4C1B_SOHC	4	4	4
4C1B_OHV	4	4	4
4C2B	4	4	4
4C2B_SOHC	4	4	4
4C2B_OHV	4	4	4
5C1B	5	-	5
5C1B_SOHC	5	-	5
6C1B	6	4 or 5	6
6C1B_SOHC	6	-	6
6C1B	6	-	6
6C1B_OHV	6	-	6
6C2B	6	6	6
6C2B SOHC	6	6	6
6C2B_OHV	6	6	6
8C2B_	8	8	8
8C2B SOHC	8	8	8
8C2B_OHV	8	8	8
10C2B	10	-	10
10C2B SOHC	10	8	10
10C2B_OHV	10	-	10

Having a large number of technologies modeled allows us to accurately characterize technologies present on engines in the analysis fleet. This collection of technologies represents the best available information we have, at the time of this action, regarding both currently available engine technologies and engine technologies that could be feasible for application to the U.S. fleet during the rulemaking timeframe. We believe this effort has yielded the most technology-rich and accurate analysis fleet utilized in the CAFE Model to date.

It is important to note that advanced engine technologies can include some of the basic engine technologies. For example, VVT is found in virtually all engines on the market and is inherent to all basic engines, all advanced engines, and all strong hybrids in the CAFE Model; only BEVs do not have VVT since they do not have engine valves. Further details on which technologies are included for each advanced engine can be found in Chapter 3.1.1.2.

3.1.3. Engine Adoption Features

Engine adoption features are defined through a combination of technology path logic, refresh and redesign cycles, phase-in capacity limits, and SKIP logic. Figure 3-1 and Figure 3-2 show the technology paths available for light-duty and HDPUV engines in the CAFE Model. Engine technology development and application typically results in an engine design moving from the basic engine tree to one of the advanced engine trees. Once an engine design moves to the advanced engine tree it is not allowed to move to alternate advanced engine trees. Table 3-18 and Table 3-19 provide a brief description of each technology and details about when a technology can be applied for the first time or indicates if a technology can only be assigned as an initial technology. Technologies applicable only during a platform redesign can be applied during a platform refresh, if another vehicle platform that shares engine codes (i.e., uses the same engine) has already applied the technology during a redesign, first. For example, models of the GMC Acadia and the Cadillac XT4 use the same engine (represented by engine code 112011 in the Market Data Input File); if the XT4 adds a new engine technology during a redesign, then the Acadia may also add the same engine technology during the next refresh or redesign. This allows the model to maintain engine sharing relationships while also maintaining refresh and redesign schedules. See Chapter 2.2.1.7 for more discussion on platform refresh and redesign cycles.

Table 3-18: LD Technology Application Schedule

Technology	Application Level	Application Schedule	Description
SOHC	Engine	Initial Only	Single Overhead Camshaft Engine
DOHC	Engine	Initial Only	Double Overhead Camshaft Engine
OHV	Engine	Initial Only	Overhead Valve Engine (maps to SOHC)
VVL	Engine	Redesign Only	Variable Valve Lift
SGDI	Engine	Redesign Only	Stoichiometric Gasoline Direct Injection
DEAC	Engine	Redesign Only	Cylinder Deactivation
TURBO0	Engine	Redesign Only	Turbocharging and Downsizing, Level 0
TURBOE	Engine	Redesign Only	Turbocharging and Downsizing, Level 0 with Cooled Exhaust Gas Recirculation
TURBOD	Engine	Redesign Only	Turbocharging and Downsizing, Level 0 with Cylinder Deactivation
TURBO1	Engine	Redesign Only	Turbocharging and Downsizing, Level 1
TURBO2	Engine	Redesign Only	Turbocharging and Downsizing, Level 2
TURBOAD	Engine	Redesign Only	Turbocharging and Downsizing with ADEAC
HCR	Engine	Redesign Only	High Compression Ratio Engine, Level 0
HCRE	Engine	Redesign Only	High Compression Ratio Engine, Level 0 with Cooled Exhaust Gas Recirculation
HCRD	Engine	Redesign Only	High Compression Ratio Engine, Level 0

			with Cylinder Deactivation
ADEACS	Engine	Redesign Only	Advanced Cylinder Deactivation with Single Overhead Camshaft
ADEACD	Engine	Redesign Only	Advanced Cylinder Deactivation with Dual Overhead Camshaft
ADSL	Engine	Redesign Only	Advanced Diesel
DSLI	Engine	Redesign Only	Advanced Diesel with Cylinder Deactivation
VCR	Engine	Redesign Only	Variable Compression Ratio Engine
VTG	Engine	Redesign Only	Variable Turbo Geometry
VTGE	Engine	Redesign Only	Variable Turbo Geometry (Electric)
CNG	Engine	Initial Only	Compressed Natural Gas Engine

Table 3-19: HDPUV Technology Application Schedule

Technology	Application Level	Application Schedule	Description
SOHC	Engine	Initial Only	Single Overhead Camshaft Engine
DOHC	Engine	Initial Only	Double Overhead Camshaft Engine
OHV	Engine	Initial Only	Overhead Valve Engine (maps to SOHC)
SGDI	Engine	Redesign Only	Stoichiometric Gasoline Direct Injection
DEAC	Engine	Redesign Only	Cylinder Deactivation
TURBO0	Engine	Redesign Only	Turbocharging and Downsizing, Level 0
ADSL	Engine	Redesign Only	Advanced Diesel
DSLI	Engine	Redesign Only	Advanced Diesel with Cylinder Deactivation

Engine technology adoption also depends on technology path and phase-in caps. Figure 3-7 and Figure 3-8 show the light-duty and HDPUV flowcharts of how engines can progress from one engine path to another. These paths are primarily tied to ease of implementation of additional technology and how closely related the technologies are. Table 3-20 and Table 3-21 details the light-duty and HDPUV phase-in caps that apply to engine technology. Few of the caps in the model would restrict implementation of engine technology during the rulemaking timeframe. In reality, the phase-in caps are not binding because the model has several other less advanced technologies available to apply first at a lower cost, as well as the redesign schedules. As discussed earlier in Chapter 2.2, 100 percent of the analysis fleet will not redesign by 2023, which is the last year that phase-in caps could apply to the engine technologies discussed in this subchapter.

Figure 3-7: LD Engine Path Flowchart

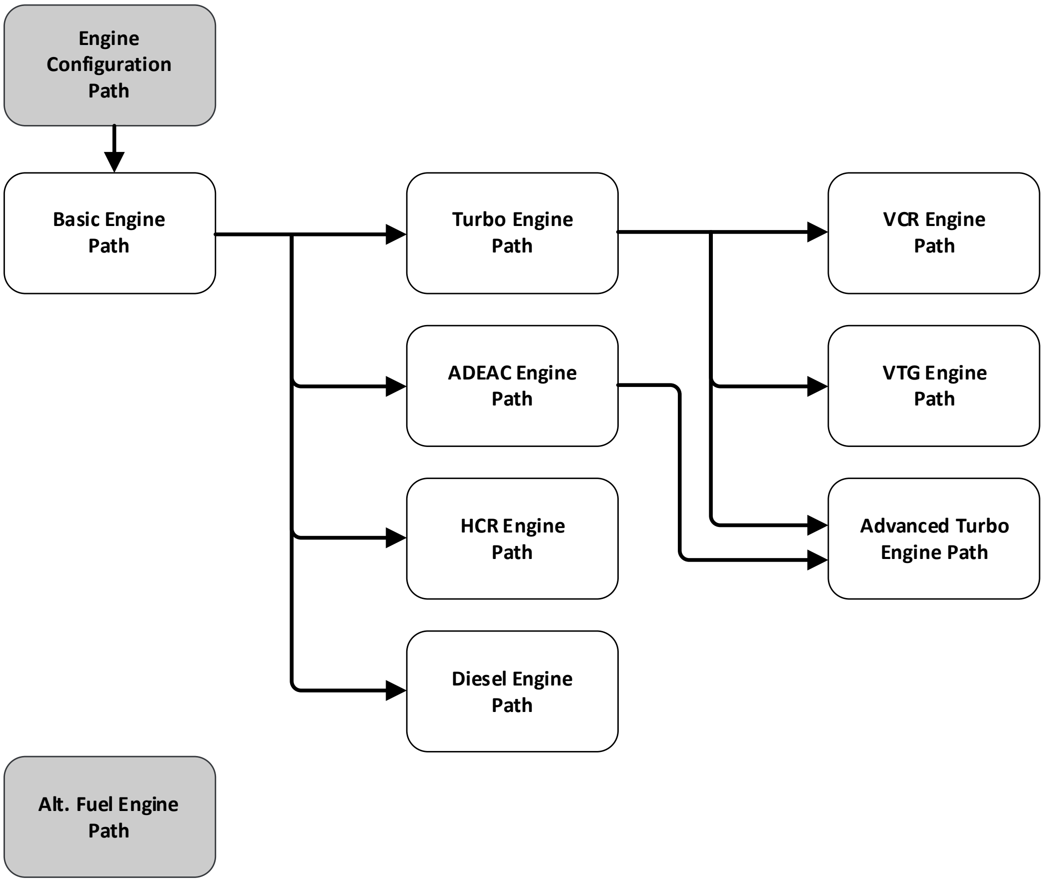

Figure 3-8: HDPUV Engine Path Flowchart

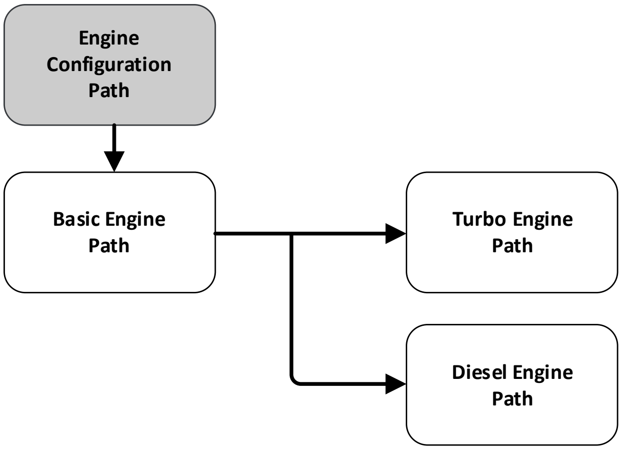

Table 3-20: LD Engine Technology Phase-In Caps

Technology	Technology Pathway	Phase-In Cap	Phase-In Start Year	First Year 100% Phase-In Allowed
VVL	Basic Engine	100%	2000	2000
SGDI	Basic Engine	100%	2000	2000
DEAC	Basic Engine	100%	2004	2004

TURBO0	Turbo Engine	100%	2004	2004
TURBOE	Turbo Engine	100%	2016	2016
TURBOD	Turbo Engine	20%	2019	2023
TURBO1	Turbo Engine	100%	2004	2004
TURBO2	Turbo Engine	100%	2010	2010
HCR	HCR Engine	100%	2010	2010
HCRE	HCR Engine	100%	2017	2017
HCRD	HCR Engine	100%	2017	2017
ADEACS	ADEAC Engine	34%	2019	2021
ADEACD	ADEAC Engine	34%	2019	2021
ADSL	Diesel Engine	100%	2010	2010
DSLI	Diesel Engine	100%	2010	2010
VCR	VCR Engine	20%	2019	2023
VTG	VTG Engine	34%	2016	2018
VTGE	VTG Engine	20%	2016	2020
TURBOAD	Advanced Turbo Engine	34%	2020	2022

Table 3-21: HDPUV Engine Technology Phase-In Caps

Technology	Technology Pathway	Phase-In Cap	Phase-In Start Year	First Year 100% Phase-In Allowed
SGDI	Basic Engine	100%	2000	2000
DEAC	Basic Engine	100%	2004	2004
TURBO0	Turbo Engine	100%	2004	2004
ADSL	Diesel Engine	100%	2010	2010
DSLI	Diesel Engine	100%	2010	2010

3.1.3.1. Basic Engines

Basic engine technologies in the CAFE Model for the light-duty analysis are represented by three technologies: VVL, SGDI, and DEAC. These technologies can all be applied individually or in any combination of the three. The HDPUV analysis only includes the SGDI and DEAC basic engine technologies and can be applied independently or together. An engine can jump from the basic engines path to any other engine path except the Alternative Fuel Engine Path.

3.1.3.2. Turbocharged Downsized Engines

Turbo downsizing allows manufacturers to maintain vehicle performance characteristics while reducing engine displacement and cylinder count. Any light-duty basic engine can adopt one of the TURBO engine technologies (TURBO0, TURBOE, TURBOD, TURBO1, and TURBO2) and any HDPUV basic engine can adopt TURBO0. Vehicles that have turbocharged engines in the model year 2022 analysis fleet will stay on the Turbo Engine Path to prevent unrealistic engine technology change in the short timeframe considered in the rulemaking analysis. TURBO technology is a mutually exclusive technology in that it cannot be adopted for HCR, diesel, ADEACs, or CNG engines.

3.1.3.3. High Compression Ratio Engines

HCR engines are a collection of engines in the HCR engine pathway (HCR, HCRE, and HCRD) for the light-duty analysis.[293] HCR engines excel in lower power applications for lower load conditions, such as driving around a city or steady state highway driving without large payloads, thus their adoption is more limited than some other technologies.

There are three categories of adoption features specific to the HCR engine pathway:

First, we do not allow vehicles with 405 or more HP to adopt HCR engines due to their prescribed power needs being more demanding and likely not supported by the lower power density found in HCR-based engines.[294] To model parts sharing, we also do not allow vehicles to adopt HCR engine if those vehicles share an engine with vehicles with 405 or more HP. Because LIVC essentially reduces the engine's displacement to make more power and keep the same levels of LIVC, manufacturers would need to increase the displacement of the engine to make the necessary power. We do not believe manufacturers will increase the displacement of their engines to accommodate HCR technology adoption.[295] Separately, as seen in the model year 2022 analysis fleet, manufacturers generally use HCR engines in applications where the vehicle's power requirements fall significantly below our HP threshold. In fact, the HP average for the sales weighted average of vehicles in the model year 2022 analysis fleet that use HCR Engine Path technologies is 179 hp, demonstrating that HCR engine use has indeed been limited to lower-hp applications, and well below our 405 hp threshold. In fringe cases where a vehicle classified as having higher load requirements does have an HCR engine, it is coupled to a hybrid system.[296] For more detailed discussion on this, see Chapter 3.1.1.2.3.

Secondly, we exclude pickup trucks and vehicles that share engines with pickup trucks from receiving IC-only HCR engines; subject to other adoption features discussed in Chapter 3.3 below, pickup trucks and vehicles that share engines with pickup trucks can receive HCR-based engine technologies in the Hybridization Paths Collection of technologies. We exclude pickup trucks from receiving IC-only HCR technology because these often-heavier vehicles have higher low speed torque needs, higher base road loads, increased payload and towing requirements, and have powertrains that are sized and tuned to perform this additional work above what passenger cars are required to conduct. As a result of the higher road loads, payloads, and towing requirements, these vehicle's engines are unable to apply enough LIVC for long enough to achieve the level of effectiveness suitable for the HCR technology.[297] We assume that a manufacturer intending to apply HCR technology to their pickup truck or vehicle that shares an engine with a pickup truck would do so in combination with an electric system to assist with the vehicle's load needs, and indeed the only manufacturer that has an HCR-like engine in its pickup truck in the model year 2022 analysis fleet has done so. We exclude vehicles that share engines with pickup trucks form receiving IC-only HCR technology to model parts sharing decisions.

Finally, we restrict HCR engine application for some manufacturers that are heavily performance-focused and have demonstrated a significant commitment to power dense technologies such as turbocharged downsizing.[298] This means that no vehicle manufactured by these manufacturers can receive an HCR

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[293] Note that there is no HCR engine pathway for HDPUVs (see Chapter 3.1.1.2.3.1 above), so there are no HCR engine adoption features for the HDPUV analysis.
[294] Heywood, J.B. 2018. Internal Combustion Engine Fundamentals. McGraw-Hill Education. Chapter 5.
[295] This bears out in industry trends: total engine size (or displacement) is at an all-time low, and trends show that industry focus on turbocharged downsized engine packages are leading to their much higher market penetration. See 2023 EPA Trends Report at 48, 78. Furthermore, increasing an engine's displacement increases fuel consumption, and thus offsets some of the fuel-economy gains a manufacturer would be seeking to obtain by using an HCR engine in the first place.
[296] See the Ford Maverick HEV. The reported total system HP for the Ford Maverick HEV is also 191hp, well below our 405hp threshold. See also the Lexus LC/LS 500h. The Lexus LC/LS 500h also uses premium fuel to reach this performance level.
[297] Supplemental Comments of Toyota Motor North America, Inc., Notice of Proposed Rulemaking: Safer Affordable Fuel-Efficient Vehicles Rule, Docket ID Numbers: NHTSA-2018-0067 and EPA-HQ-OAR-2018-0283. "Tacoma has a greater coefficient of drag from a larger frontal area, greater tire rolling resistance from larger tires with a more aggressive tread, and higher driveline losses from 4WD. Similarly, the towing, payload, and off road capability of pick-up trucks necessitate greater emphasis on engine torque and HP over fuel economy.
This translates into engine specifications such as a larger displacement and a higher stroke-to-bore ratio (see Table 3-1). Tacoma's higher road load and more severe utility requirements push engine operation more frequently to the less efficient regions of the engine map and limit the level of Atkinson operation…This endeavor is not a simple substitution where the performance of a shared technology is universal.
Consideration of specific vehicle requirements during the vehicle design and engineering process determine the best applicable powertrain."
[298] There are three manufacturers that met the criteria (near 100 percent turbo downsized fleet, and future hybrid systems are based on turbo-downsized engines) described and were excluded: BMW, Daimler, and JLR.

engine. Again, we implement this adoption feature to avoid an unquantified amount of stranded capital that would be realized if these manufacturers switched from one technology to another.

The P2 technologies that use HCR engines use similar adoption features and are discussed separately in Chapter 3.3.

3.1.3.4. Advanced Cylinder Deactivation Technology

ADEACS and ADEACD technology (e.g., Dynamic Skip Fire), can be applied to any engine in the light-duty analysis with basic technology but would follow the assigned camshaft architecture configuration. Basic SOHC engines can move to ADEACS technology and basic DOHC engines can move to the ADEACD technology. This technology represents a naturally aspirated engine with ADEAC with either a SOHC (ADEACS) or DOHC (ADEACD) engine architecture. Additional technology can be applied to these engines by moving to the Advanced Turbo Engine Path.

3.1.3.5. Miller Cycle Engines

Miller cycle (VTG and VTGE) engines can be applied to any basic and turbocharged engine in the light-duty analysis. VTGE technology is enabled using a 48V system that presents an improvement from traditional turbocharged engines, and accordingly VTGE includes the application of a mild hybrid (BISG) system.

3.1.3.6. Variable Compression Ratio Engines

VCR engines can be applied to basic and turbocharged engines in the light-duty analysis, but the technology is not applicable to mild hybrids and is limited to OEMs and partnered OEMs that have already implemented the technology.[299] VCR technology requires a complete redesign of the engine, and in the analysis fleet, only two of Nissan's models had incorporated this technology.

Few manufacturers and suppliers provided information about VCR technologies, and we reviewed several design concepts that could achieve a similar functional outcome. In addition to design concept differences, intellectual property ownership complicates the ability to define a VCR hardware system that could be widely adopted across the industry. VCR engines are complex, costly by design, and address many of the same efficiency losses as mainstream technologies like downsize turbocharging, making it unlikely that a manufacturer that has already started down an incongruent technology path would adopt VCR technology. Because of these issues, we limited adoption of the VCR engine technology to OEMs that have already employed the technology and their partners. We do not believe any other manufacturers will invest to develop and market this technology in their fleet in the rulemaking timeframe.

3.1.3.7. Advanced Turbocharged Downsized Engines

Advanced turbo engines are becoming more prevalent as the technologies mature. In the light-duty analysis, the advanced turbo technology is TURBOAD. TURBOAD combines TURBO0 and ADEACD technologies. Engines from either the Turbo Engine Path or the ADEAC Engine Path can adopt this technology.

3.1.3.8. Diesel Engines

Any basic engine can adopt ADSL and DSLI engine technologies in either the light-duty or HDPUV analyses. In our engineering judgement for the light-duty fleet, this is a rather complex and costly technology to adopt, and it would take significant investment for a manufacturer to develop. For more than a decade, diesel engine technologies have been used in less than one percent of the total light-duty fleet production, though they are more commonly found in HDPUV vehicles where the technology is found in more than a third of our starting analysis fleet.

[299] Nissan and Mitsubishi are strategic partners and members of the Renault-Nissan-Mitsubishi Alliance.

3.1.3.9. Alternative Fuel Engines

CNG engines are a base level-only engine technology and cannot be applied in the analysis. We currently do not have any information indicating that this is a technology that manufacturers will employ to improve fuel economy in the rulemaking timeframe. Separately, because CNG is considered an alternative fuel under EPCA/EISA, it cannot be adopted during the rulemaking timeframe in the standard-setting analysis.

3.1.4. Engine Effectiveness

The CAFE Model considers both effectiveness and cost in selecting any technology changes. Technology effectiveness is the fuel consumption reduction achieved by changing a vehicle from one combination of technologies to another combination of technologies, see Chapter 2.4.

We simulate effectiveness values for engine technologies in two ways. We either calculate the value based on the difference in full vehicle simulation results created using the Autonomie modeling tool, or we determine the effectiveness values using an alternate calculation method, including analogous improvement values based on Autonomie modeling for similar technologies.

The effectiveness values for the engine technologies, for all ten light-duty vehicle technology classes, are shown in Figure 3-9 and Figure 3-10. The HDPUV technology effectiveness values can be found in Figure 3-11. Each of the effectiveness values shown is representative of the improvements seen for upgrading only the listed engine technology for a given combination of other technologies. In other words, the range of effectiveness values seen for each specific technology (e.g., TURBO1) represents the addition of the TURBO1 technology to every technology combination that could select the addition of TURBO1. See Table 3-22 for several specific examples. We show the change in fuel consumption values between entire technology keys,[300] and not the individual technology effectiveness values. Using the change between whole technology keys captures the complementary or non-complementary interactions among technologies.

Table 3-22: Example of Effectiveness Calculations Shown in Figure 3-9

Tech	Vehicle Tech Class	Initial Technology Key	Fuel Consumption		Effectiveness (%)
			Initial (gal/mile)	New (gal/mile)	
TURBO1	Medium Non-Performance	DOHC;;;;;;AT8L2;SS12V; ROLL10;AERO5;MR2	0.02835	0.02501	11.78
TURBO1	Medium Non-Performance	DOHC;;;;;;AT8L2;CONV; ROLL10;AERO5;MR2	0.02927	0.02556	12.68
TURBO1	Medium Non-Performance	DOHC;;;;;;AT8L2;BISG; ROLL10;AERO5;MR2	0.02753	0.02393	13.08
TURBO1	Medium Non-Performance	DOHC;;;;;;AT6;SS12V; ROLL10;AERO5;MR2	0.03049	0.02690	11.77
*The 'Tech' is added to the 'Initial Technology Key' replacing the existing engine technology, resulting in the new fuel consumption value. The percent effectiveness is found by determining the percent improved fuel consumption of the new value versus the initial value.[301]					

[300] Technology key is the unique collection of technologies that constitutes a specific vehicle, see Chapter 2.3.6.
[301] The full data set we used to generate this example can be found in the CAFE Model Fuel Economy Adjustment Files.

Figure 3-9: Engine Technology Effectiveness Values for All LD Vehicle Technology Classes (Unconstrained)

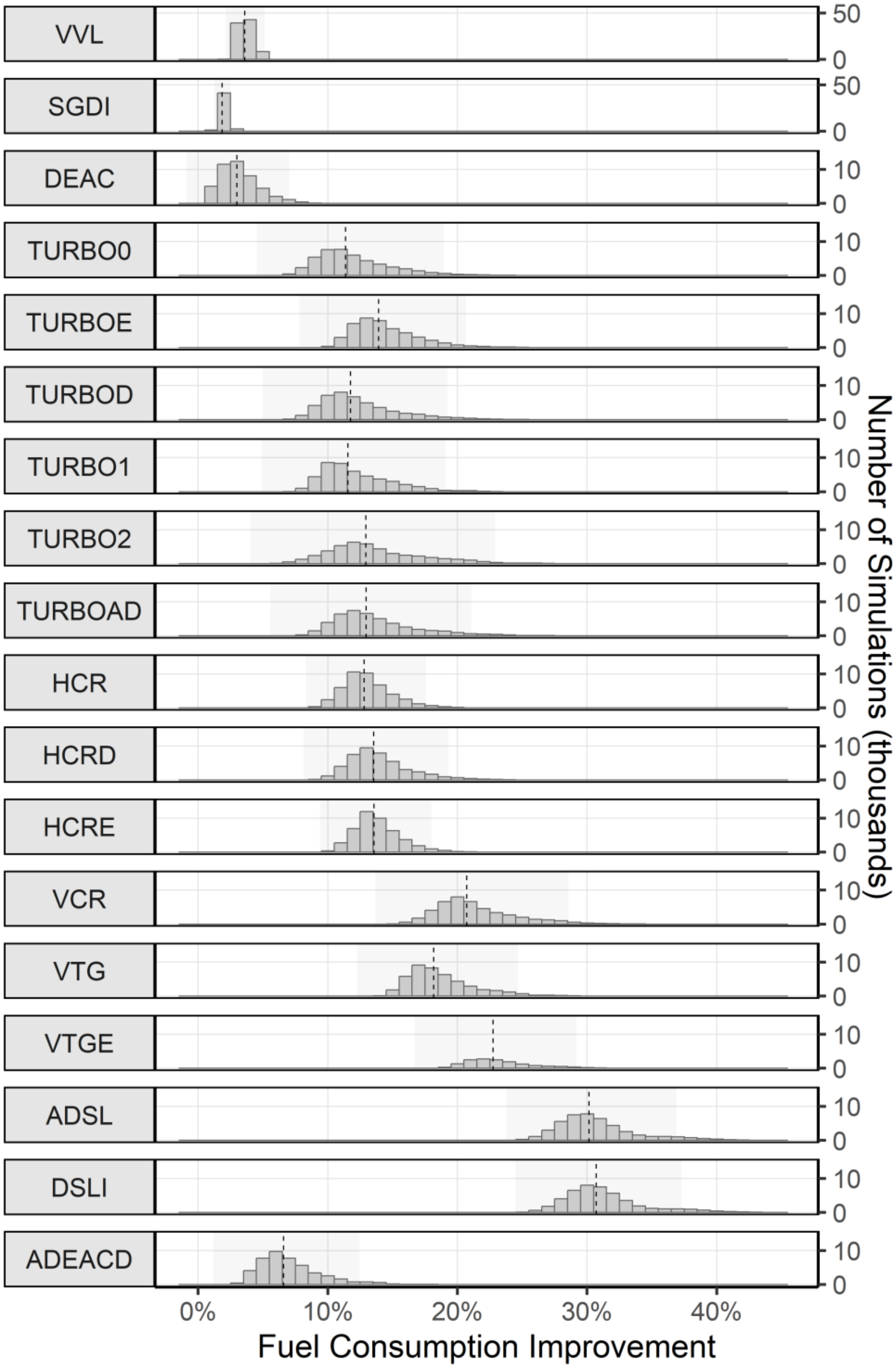


Figure 3-10: Engine Technology Effectiveness Values for All LD Vehicle Technology Classes (Standard Setting)

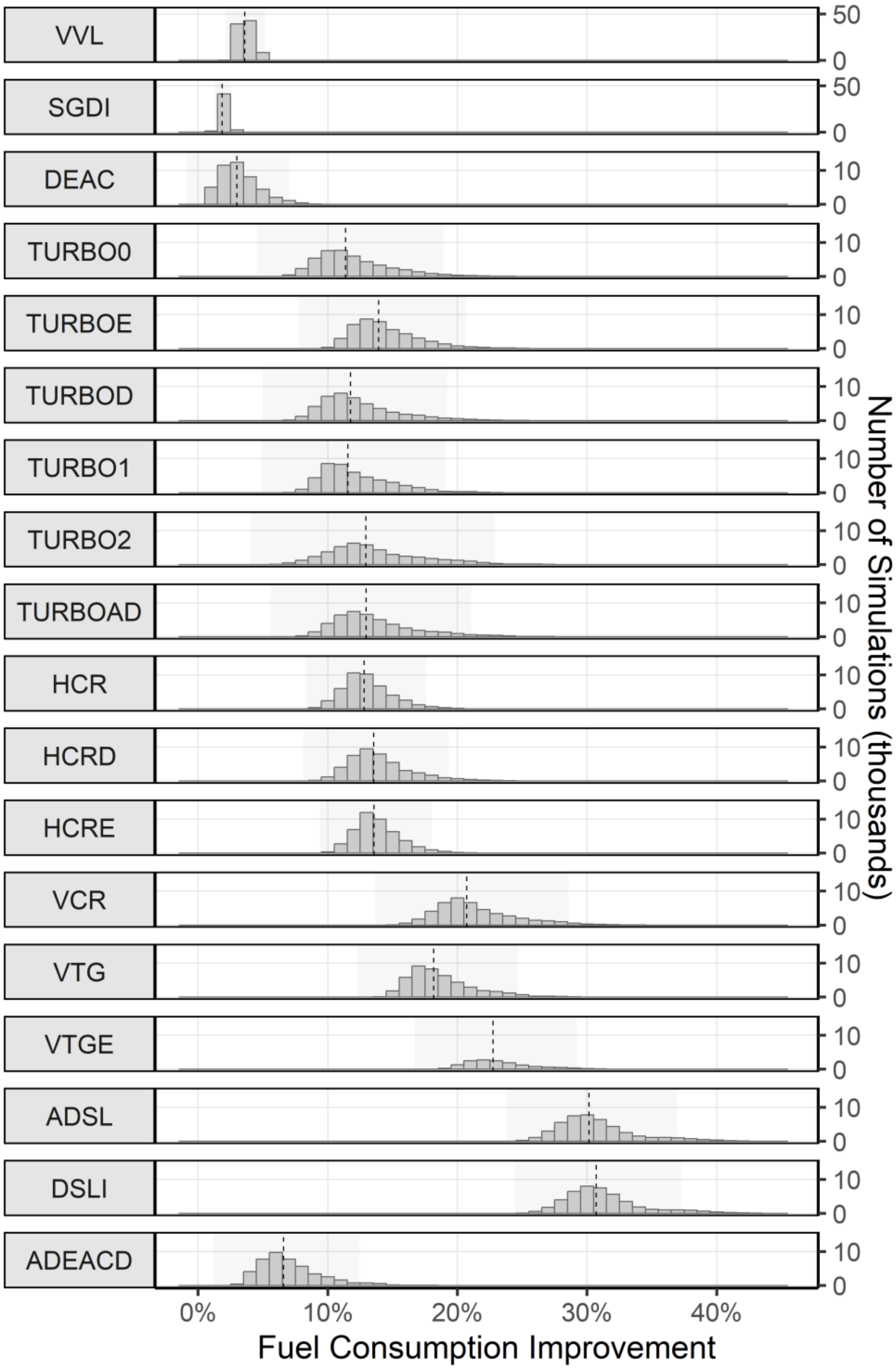
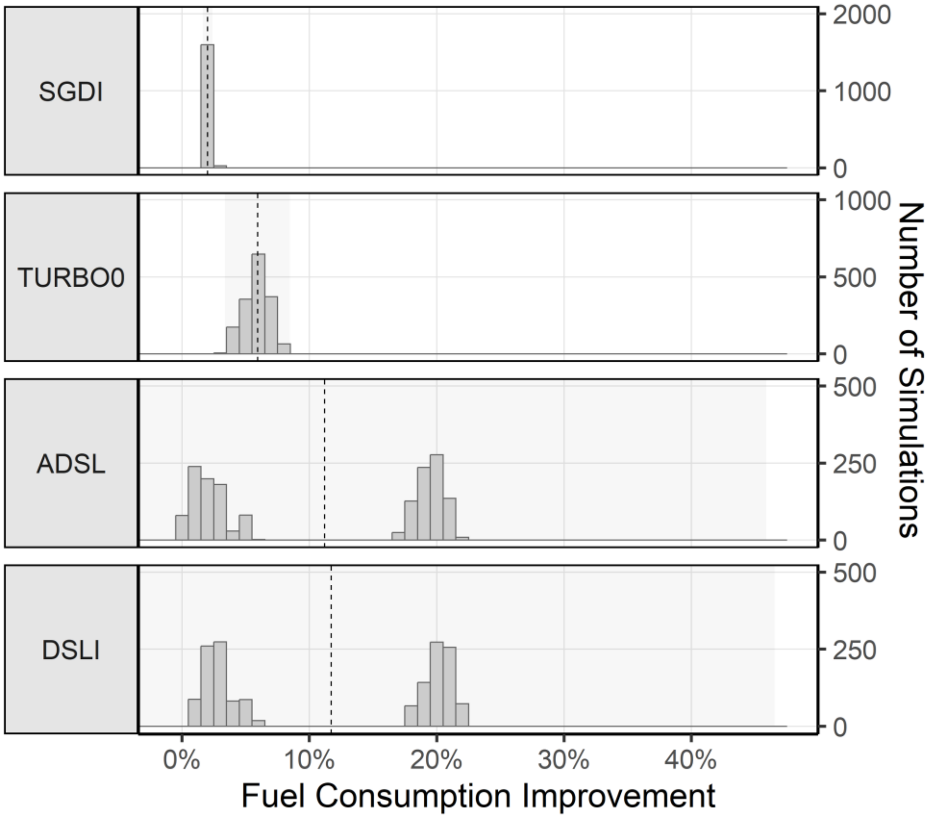


Figure 3-11: Engine Technology Effectiveness Values for All HDPUV Vehicle Technology Classes



The following subchapters discuss how we determined the effectiveness of the engine technologies on the simulated vehicle system's performance in the rulemaking analysis. We first discuss the values determined directly from the Autonomie simulations, followed by the values that are determined using alternative modeled approaches.

3.1.4.1. Autonomie Modeled Values

The Autonomie model's full vehicle simulation results provide most of the effectiveness values that we use as inputs to the CAFE Model. For a full discussion of the Autonomie modeling see Chapter 2.3. The Autonomie modeling uses engine map models as the primary inputs for simulating the effects of different engine technologies.

Engine maps provide a three-dimensional representation of engine performance characteristics at each engine speed and load point across the operating range of the engine. Engine maps have the appearance of topographical maps, typically with engine speed on the horizontal axis and engine torque, power, or BMEP[302] on the vertical axis. A third engine characteristic, such as BSFC,[303] is displayed using contours overlaid across the speed and load map. The contours provide the values for the third characteristic in the regions of operation covered on the map. Other characteristics typically overlaid on an engine map include engine emissions, engine efficiency, and engine power. We refer to the engine maps developed to model the behavior of the engines in this analysis as engine map models.

The engine map models we use in this analysis are representative of technologies that are currently in production or are expected to be available in the rulemaking timeframe. We develop the engine map models to be representative of the performance achievable across industry for a given technology, and they are not intended to represent the performance of a single manufacturer's specific engine. We target a broadly

[302] BMEP is an engineering measure, independent of engine displacement, that indicates the actual work an engine performs.
[303] Brake-specific fuel consumption is the rate of fuel consumption divided by the power being produced.

representative performance level because the same combination of technologies produced by different manufacturers will have differences in performance, due to manufacturer-specific designs for engine hardware, control software, and emissions calibration.

Accordingly, we expect that the engine maps developed for this analysis will differ from engine maps for manufacturers' specific engines. However, we intend and expect that the incremental changes in performance modeled for this analysis, due to changes in technologies or technology combinations, will be similar to the incremental changes in performance observed in manufacturers' engines for the same changes in technologies or technology combinations.

Note that we never apply absolute BSFC levels from the engine maps to any vehicle model or configuration for the rulemaking analysis. We only use the absolute fuel economy values from the full vehicle Autonomie simulations to determine incremental effectiveness for switching from one technology to another technology. The incremental effectiveness is applied to the absolute fuel economy or fuel consumption value of vehicles in the analysis fleet, which are based on CAFE or FE compliance data. For subsequent technology changes, we apply incremental effectiveness changes to the absolute fuel economy level of the previous technology configuration. Therefore, for a technically sound analysis, it is most important that the differences in BSFC among the engine maps be accurate, and not the absolute values of the individual engine maps. However, achieving this can be challenging.

For this analysis, we use a small number of base level engine configurations with well-defined BSFC maps, and then, in a very systematic and controlled process, add specific, well-defined technologies to create a BSFC map for each unique technology combination. This could theoretically be done through engine or vehicle testing, but we would need to conduct tests on a single engine, and each configuration would require physical parts and associated engine calibrations to assess the impact of each technology configuration, which is impractical for the rulemaking analysis because of the extensive design, prototype part fabrication, development, and laboratory resources that are required to evaluate each unique configuration. We and the automotive industry use modeling as an approach to assess an array of technologies with more limited testing. Modeling offers the opportunity to isolate the effects of individual technologies by using a single or small number of base level engine configurations and incrementally adding technologies to those base level configurations. This provides a consistent reference point for the BSFC maps for each technology and for combinations of technologies that enables us to carefully identify and quantify the differences in effectiveness among technologies.

The CAFE Analysis Autonomie Documentation provides a detailed discussion on how the Autonomie model uses engine map models as inputs to the full vehicle simulations. Additionally, the CAFE Analysis Autonomie Documentation contains the engine map model topographic figures, and additional engine map model data can be found in the Autonomie Inputs and Assumptions Description Files.[304]

3.1.4.1.1. Engine Map Models

For the LD engines, IAV GmbH (IAV) Engineering developed most of the engine map models we use in this analysis. IAV is one of the world's leading automotive industry engineering service partners with an over 35-year history of performing research and development for powertrain components, electronics, and vehicle design.[305] The primary outputs of IAV's work for this analysis are engine maps that model the operating characteristics of engines equipped with specific technologies.

SwRI developed the HDPUV and the light-duty diesel engine maps for this analysis. SwRI has been providing automotive science, technology, and engineering services for over 70 years.[306] Much like the approach IAV has taken to develop the light-duty engine maps, SwRI has followed a similar approach to

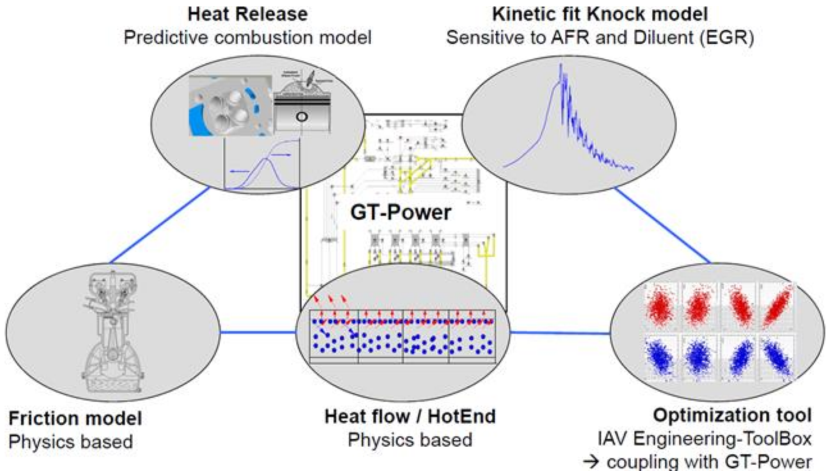
[304] See the following files which can be found in the rulemaking docket by filtering for Supporting & Related Materials: ANL - All Assumptions_Summary_NPRM_2206.xlsx; ANL - Data Dictionary_NPRM_2206.xlsx; ANL - Summary of Main Component Performance, Assumptions_NPRM_2206.xlsx; ANL - All Assumptions_Summary_NPRM_2206.xlsx; ANL - Data Dictionary_NPRM_2206.xlsx; ANL - Summary of Main Component Performance, Assumptions_NPRM_2206.xlsx; ANL – All Assumptions Summary – (2b-3) FY22 NHTSA – 220811.xlsx; ANL – Data Dictionary – (2b-3) FY22 NHTSA – 2200811.xlsx' ANL – Summary of Main Component Performance Assumptions – (2b-3) FY22 NHTSA – 220811.xlsx.
[305] IAV Automotive Engineering. Available at: https://www.iav.com/en. (Accessed: Feb. 8, 2024).
[306] Southwest Research Institite. Available at: https://www.swri.org. (Accessed: Feb. 8, 2024)

developing the light-duty and HDPUV engine models using GT-POWER as discussed in the paragraphs below.

IAV and SwRI developed the engine map models using the GT-POWER© Modeling tool (GT-POWER). GT-POWER is a commercially available, industry standard, engine performance simulation tool. GT-POWER can be used to predict detailed engine performance characteristics such as power, torque, airflow, volumetric efficiency, fuel consumption, turbocharger performance and matching, and pumping losses.[307] IAV developed the engine maps using software within the GT-Suite developed by Gamma Technologies. IAV's GT-POWER engine modeling includes sub-models to enforce operating constraints for the engine. The sub-models interface with the base GT-POWER model as shown in Figure 3-12, and are listed below.

- Heat release through a predictive combustion model
- Knock characteristic through a kinetic fit knock model
- Physics-based heat flow model
- Physics-based friction model
- IAV's proprietary Optimization Toolbox[308]

Figure 3-12: Overview of the Engine Model and Sub-Models Used to Develop Engine Maps



IAV uses benchmark production engine test data, component test data, and manufacturers and suppliers technical publications to develop a one-dimensional GT-POWER engine model that serves as the initial, or root, engine technology configuration (Eng01) for the maps in this analysis. IAV then incrementally adds technologies to the root model to create the families of engine map models. IAV develops each new engine model using a similar overall method. IAV defines the characteristics of the root engine, Eng01 in the case of basic DOHC engines, and optimizes the root engine's combustion parameters while minimizing fuel consumption and maintaining performance. IAV then uses the optimized engine model to simulate operation and develop a BMEP/BSFC-based engine map for the modeled engine.

IAV then starts with the root engine model (Eng01, DOHC VVT only) and integrates a new technology, such as SGDI. IAV re-optimizes the new engine (Eng18, DOHC VVT+SGDI) for all combustion parameters while minimizing fuel consumption and maintaining performance. IAV then again uses the resultant new engine model to simulate operation and develop a new BMEP/BSFC based engine map, in this case Eng18. The new engine map (Eng18) can then be directly compared to the root engine map (Eng01) and the differences in those engine maps specifically shows the impact of adding the SGDI technology. IAV repeats this process

[307] For additional information on the GT-POWER tool please see: https://www.gtisoft.com/gt-suite-applications/propulsion-systems/gt-power-engine-simulation-software. (Accessed: Feb. 8, 2024).
[308] IAV's Optimization Toolbox is a module of IAV Engine. IAV Engine is the basic platform for designing engine mechanics and provides many tools that have proven their worth across the globe in several decades of automotive development work at IAV. The modules help designers, computation engineers and simulation specialists in designing mechanical engine components—for example, in laying out valvetrains and timing gears as well as crankshafts.

starting from each of the root engine maps to create the engine technology groups discussed in Chapter 3.1.2 and Chapter 3.1.3, see Table 3-23 and Table 3-24 for information about all engine maps.

IAV uses the following initial engine modeling assumptions and techniques across the sub-models to isolate the effect of adding technologies to an engine.

- All gasoline engine optimization assumes the use of Tier 3 (E10 87 Anti-Knock Index (AKI))[309] fuel to ensure the engines are capable of operating on regular gasoline (87 pump octane = (R+M)/2).[310,311]
- Ambient conditions are fixed at 25 degrees C and 990 mbar barometric pressure.
- Relevant engine geometries/parameters are measured and modeled with friction/flow losses, heat transfer, etc. and calibrated to match measurements.
- Displacement normalized mechanical friction is modeled as a function of engine speed and specific load.
- A combustion model is trained and used to predict fuel heat release rate in response to physical effects such as cylinder geometry, pressure, temperature, turbulence, residual gas concentration, etc.
- The combustion stability model is trained using Coefficient of Variation (COV) of Indicated Mean Effective Pressure (IMEP)[312,313] data to estimate EGR tolerance and to identify the maximum amount of EGR that may be used without adversely impacting vehicle drivability, especially at low loads.
- The behavior of engine air intake and exhaust systems and fuel injection systems is simulated by developing load controllers for fuel/air path actuators. Engine combustion control, through use of onboard sensors, is simulated by developing targeting controllers to drive optimal combustion phasing, constrained by knock, just as in a physical engine.
- Careful modeling practice is used to provide confidence that calibrations will scale and predict reasonable and reliable values as parameters are changed across the various engine technology combinations.

Before use in the Autonomie analysis, both IAV and SwRI validate the generated engine maps against a global database of benchmarked data, engine test data, single cylinder test data, prior modeling studies, technical studies, and information presented at conferences.[314] IAV and SwRI also validate the effectiveness values from the simulation results against detailed engine maps produced from the Argonne engine benchmarking programs, as well as published information from industry and academia, which ensures reasonable representation of simulated engine technologies.[315,316]

IAV and SwRI provide the families of engine BMEP/BSFC maps to Argonne as an input for the full vehicle modeling and simulation for the light-duty and HDPUV analyses. For a full discussion on how Argonne integrates the engine map models into the Autonomie simulations, refer to the CAFE Analysis Autonomie Documentation.[317] The light-duty and HDPUV engine map models that we use in this analysis and their specifications are shown in Table 3-23 and Table 3-24.

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309 Currently, throughout the United States, pump fuel is a blend of 90 percent gasoline and 10 percent ethanol.

310 Octane rating or the AKI rating of the fuel is expressed as the average of Research Octane + Motor Octane (R+M/2). In the United States, typically there are three distinct grades of fuel available, each provides a different octane rating. In most regions of the United States, the lowest octane fuel is 87 AKI, midgrade typically 89-90 AKI, and premium 91-94 AKI. In higher altitude regions, the lowest octane fuel is typically 85 AKI.

311 EIA. 2022. Octane in Depth. Last revised: Nov. 17, 2022. Available at: https://www.eia.gov/energyexplained/gasoline/octane-in-depth.php. (Accessed: Feb. 8, 2024).

312 Indicated Mean Effective Pressure (IMEP) is the mean effective pressure calculated with indicated (theoretical) power of the engine.

313 Industry and researchers use a measurement known as coefficient of variation of indicated mean effective pressure (COV of IMEP) to evaluate combustion stability.

314 Friedrich, I. et al. 2006. Automatic Model Calibration for Engine-Process Simulation with Heat-Release Prediction. SAE Technical Paper 2006-01-0655. Available at: https://doi.org/10.4271/2006-01-0655. (Accessed: Feb. 8, 2024);
Rezaei, R. et al. 2012. Zero-Dimensional Modeling of Combustion and Heat Release Rate in DI Diesel Engines. *SAE International Journal of Engines*. Vol. 5(3): at 874-85. Available at: https://doi.org/10.4271/2012-01-1065. (Accessed: May 31, 2023); Berndt, R. et al. 2015. Multistage Supercharging for Downsizing with Reduced Compression Ratio. *MTZ Worldwide*. Vol. 76: at 10-15. Available at: https://link.springer.com/article/10.1007/s38313-015-0036-4.; Neukirchner, Heiko. et al. 2014. Symbiosis of Energy Recovery and Downsizing. *MTZ Worldwide.* Vol. 75: at. 4-9. Available at: https://link.springer.com/article/10.1007/s38313-014-0219-4.

315 Bottcher, L., Grigoriadis, P. 2019. ANL – BSFC map prediction Engines 22-26. National Highway Traffic Safety Association. Available at: https://lindseyresearch.com/wp-content/uploads/2021/09/NHTSA-2021-0053-0002-20190430_ANL_Eng-22-26-Updated_Docket.pdf. (Accessed: Feb. 8, 2024).

316 Reinhart, T. 2022. Engine Efficiency Technology Study. Final Report. SwRI Project No. 03.26457.

317 Islam, E. S. et al. Vehicle Simulation Process to Support the Analysis for model year 2027 and Beyond CAFE and model year 2030 and Beyond HDPUV FE Standards. ANL/TAPS-23/2.

Table 3-23: Light-Duty Engine Map Models Used in This Analysis

Engines	Technologies	Notes	Source
eng01	DOHC VVT	Gasoline, 2.0L, 4 cyl, NA, PFI, DOHC, VVT	IAV
eng02	DOHC VVT+VVL	VVL added to Eng01	IAV
eng03	DOHC VVT+VVL+SGDI	SGDI added to Eng02	IAV
eng04	DOHC VVT+VVL+SGDI+DEAC	Cylinder deactivation ability added to Eng03	IAV
eng5b	SOHC VVT (valvetrain friction reduction)	Eng5a with valvetrain friction reduction	IAV
eng6a	SOHC VVT+VVL (valvetrain friction reduction)	Eng02 with valvetrain friction reduction	IAV
eng7a	SOHC VVT+VVL+SGDI (valvetrain friction reduction)	Eng03 with valvetrain friction reduction	IAV
eng8a	SOHC VVT+VVL+SGDI+DEAC (valvetrain friction reduction)	Eng04 with valvetrain friction reduction	IAV
eng12	TURBO1 - DOHC Turbo 1.6L 18bar	1.6L, 4 cyl, turbocharged, SGDI, DOHC, VVT, VVL	IAV
eng13	TURBO2 - DOHC Turbo 1.2L 24bar	Eng12 downsized to 1.2L	IAV
eng14	CEGR- DOHC Turbo 1.2L 24bar + CEGR	Cooled external EGR added to Eng13	IAV
eng18	DOHC VVT + SGDI	2.0L, 4 cyl, NA, SGDI, DOHC, VVT	IAV
eng19	DOHC VVT + DEAC	Cylinder deactivation ability added to Eng01	IAV
eng20	DOHC VVT + VVL + DEAC	Cylinder deactivation ability added to Eng02	IAV
eng21	DOHC VVT + SGDI + DEAC	Cylinder deactivation ability added to Eng18	IAV
eng23b	VTG - Miller VVT+SGDI+CEGR+CR12	2.0L, 4 cyl, Miller Cycle turbo, SGDI, DOHC, VVT, VVL with VTG	IAV
eng23c	VTGe - Miller eCharger+SGDI+CEGR+CR12	2.0L, 4 cyl, Miller Cycle turbo SGDI, DOHC, VVT, eCharger	IAV
eng26	Atkinson - HEV	HEV-PHEV Atkinson Cycle Engine 1.8L	IAV
eng26a	VCR - SGDI+Turbo+CEGR+CR9/12	Gasoline, 2.0L, 4 cylinder, SGDI, variable compression ratio, with cooled EGR, VVT, turbocharged	IAV
eng32	HCR - 2.5L NA, Atkinson DOHC CR13 SGDI	2.5L, NA, high compression ratio, VVT, SGDI	IAV

eng33	HCRE - 2.5L NA Atkinson DOHC CR13 SGDI+CEGR	Cooled external EGR added to eng32	IAV
eng34	HCRD - 2.5L NA Atkinson DOHC CR13 SGDI + DEAC	Cylinder deactivation added to eng32	IAV
eng36	TURBO0 - 1.6L Turbo DOHC SGDI CR10.5	1.6L, 4 cyl, turbocharged, SGDI, DOHC, VVT	IAV
eng37	TURBOE - 1.6L Turbo DOHC SGDI CR10.5 CEGR	Cooled external EGR added to eng36	IAV
eng38	TURBOD - 1.6L Turbo DOHC SGDI CR10.5 + DEAC	Cylinder deactivation added to eng36	IAV
eng39	TURBOAD - 1.6L Turbo DOHC SGDI CR10.5 + ADEACD	Advanced cylinder deactivation added to eng36	IAV
eng40	ADEACD - 2.0L NA VVT DOHC SGDI CR11 + ADEACD	Advanced cylinder deactivation added to eng18	IAV
eng45	ADSL - 3.0L Diesel	3.0L Diesel	SWRI
eng46	DSLI - 3.0L Diesel + DEAC	Cylinder deactivation added to eng45	SWRI

Table 3-24: HDPUV Engine Map Models Used in This Analysis

Engines	Technologies	Notes	Source
eng4a	OHV VVT (CR 10.5)	Basic level with PFI and 10.5 CR from Ford 7.3L 2020	SWRI
eng4b	OHV VVT + SGDI (CR11.5)	SGDI and 11.5 compression ratio, naturally aspirated	SWRI
eng4c	DOHC VVT + SGDI + DEAC (CR11.5)	NA SGDI with DEAC and 11.5 CR	SWRI
eng4d	TURBO0 - Turbo VVT DOHC SGDI CR9.5	Turbocharged Downsized with SGDI 4V, Independent Cam Phasers (VVT)	SWRI
eng3a	ADSL - Diesel basic level for Van	Diesel from 3.0L Basic level	SWRI
eng3c	DSLI - Diesel basic level + cylinder deactivation for Van	Diesel from 3.0L Cylinder Deactivation	SWRI
eng1a	ADSL - Diesel basic level for Pickup	Diesel from 6.7L Basic level	SWRI
eng1c	DSLI - Diesel basic level + cylinder deactivation for Pickup	Diesel from 6.7L with Cylinder Deactivation	SWRI
eng45	ADSL - 3.0L Diesel for HD Vans	3.0L Diesel	SWRI
eng46	DSLI - 3.0L Diesel + DEAC for HD Vans	Cylinder deactivation added to eng45	SWRI

3.1.4.2. Alternative Modeled Values – Analogous Effectiveness Values

For most engine technologies considered in the analysis, we derive the fuel economy improvements from the database of Autonomie full-vehicle simulation results. However, the analysis also incorporates a handful of what we refer to as analogous effectiveness values. We determine analogous effectiveness values by using representative effectiveness values for a given technology when applied to a reasonably similar base engine; an example of this is the application of SGDI to the basic level SOHC engine. Currently there is no engine map model for the SOHC+SGDI engine configuration. To create the effectiveness data required as an input to the CAFE Model, first, we conduct a pairwise comparison between technology configurations that included the DOHC engine (Eng1) and the DOHC +SGDI (Eng18) engine. Then, we use the results of that comparison to generate a data set of emulated performance values for adding the SGDI technology to the SOHC engine (Eng5b) systems.

We perform the pairwise comparison by finding the difference in fuel consumption performance between every technology configuration using the analogous base technology (e.g., Eng1) and every technology configuration that only changes to the analogous technology (e.g., Eng18). The individual changes in performance between all the technology configurations are then added to the same technology configurations that use the new base technology (e.g., Eng5b) to create a new set of performance values for the new technology (e.g., SOHC+SGDI). Table 3-25 shows the engine technologies where analogous effectiveness values are used.

Table 3-25: LD and HDPUV Engine Technology Performance Values Determined by Analogous Effectiveness Values

Analogous Basic Level	Analogous Technology	New Base Technology	New Technology
Eng1 DOHC	Eng18 DOHC+SGDI	Eng5b SOHC	SOHC+SGDI
Eng1 DOHC	Eng19 SOHC+DEAC	Eng5b SOHC	SOHC+DEAC
Eng1 DOHC	Eng20 DOHC+VVL+ DEAC	Eng5b SOHC	SOHC+VVL+ DEAC
Eng1 DOHC	Eng21 DOHC+SGDI+DEAC	Eng5b SOHC	SOHC+SGDI+ DEAC

3.1.5. Engine Costs

The CAFE Model considers both cost and effectiveness in selecting any technology changes. We allocated considerable resources to sponsoring research to determine DMCs for fuel saving technologies.[318] We apply an RPE and a learning factor to the DMC values to determine the total overall cost of the technology for a given model year. The full list of engine technology costs used in this analysis, across all model years, and in 2021 dollars, can be found in the Technologies Input File. We discussed the application of RPE and CL to the DMCs in Chapter 4.

We used absolute costs in this analysis instead of relative costs, which were used prior to the 2020 CAFE rulemaking. We use absolute costs to ensure the full cost of the ICE is removed when electrification technologies are applied, specifically for the transition to BEVs. This analysis models the cost of adopting BEV technology by first removing the costs associated with IC powertrain systems, then applying the BEV system costs. Interested readers can still determine relative costs through comparison of the absolute costs for the initial technology combination and the new technology combination.

[318] FEV prepared several cost analysis studies for EPA on subjects ranging from advanced 8-speed transmissions to belt alternator starter, or start/stop systems. NHTSA contracted Electricore, EDAG, and Southwest Research for teardown studies evaluating MR and transmissions. The 2015 NAS report on fuel economy technologies for light-duty vehicles also evaluated NHTSA and EPA's technology costs developed based on these teardown studies.

The costs that we use to model the application of engine technologies can be found across multiple tabs of the Technologies Input File. We determine engine costs based on engine size and configuration, instead of vehicle technology class. We designate the engine cost tabs in the Technologies Input File based on number of cylinders and number of cylinder banks. An example of the designations is 4C1B, which is a 4-cylinder 1 bank engine; this engine configuration is more commonly known as an I-4 engine. There are also tabs for SOHC engines, OHV engines (1 camshaft per bank) and 'L' designated engines. The 'L' designation accounts for the cost of turbo downsizing for smaller engines.

The cost tabs use DOHC (2 camshafts per bank) architecture as the starting point, so the SOHC (1 camshaft per bank) engine and OHV (1 camshaft per bank) engine designations are for engines with a SOHC architecture or OHV architectures respectively. However, for costing purposes, we assume all engines are DOHC once advanced engine technologies are applied. We determine cylinder count, engine architecture, and configuration by assignment in the Market Data Input File, see Chapter 3.1.2. Table 3-26 gives a summary of some of the more common engine designations. For a full discussion about the Technologies Input File, see the CAFE Model Documentation.

Table 3-26: Summary of Common Engine Configurations in CAFE Model Input File

Engine Costing Designation	Cylinders	Camshafts	Represented Cylinder Configurations
2C1B	2	2	2-cylinder engine
3C1B	3	2	'I' configuration engine
4C1B	4	2	'I' configuration engine
4C2B	4	4	'V' or 'H' configuration engine
5C1B	5	2	'I' configuration engine
6C1B	6	2	'I' configuration engine
6C2B	6	4	'V' or 'H' configuration engine
8C2B	8	4	'V' or 'H' configuration engine

When the model applies forced-induction technology to a naturally aspirated engine, the engine has a significant boost in power density and can be reduced in size while maintaining similar performance.[319] The analysis models this reduction in engine size, and, thus, cost, by assuming a reduction in the total cylinder count when determining the absolute costs of the new engine in the Technologies Input File. For example, the cost of forced induction-based technologies (e.g., TURBO1) is found in the DOHC V8 naturally aspirated tab (8C2B) of the Technologies Input File, however, the model assumes only 6-cylinders when calculating costs. Table 3-27 provides a small example set of the costing configurations for turbo downsized technologies versus the base engine configuration costing tab.

Table 3-27: Examples of How LD and HDPUV Engine Configuration Is Assumed to Change for Cost Purposes When Turbo-Downsizing Technology Is Applied

Naturally Aspirated Costing Configurations	Turbo Downsized Costing Configuration
4C1B	4C1B*
6C2B	4C1B
8C2B	6C2B
10C2B	8C2B
* NOTE: For this analysis, cost for turbo downsizing a low output 4-cylinder naturally aspirated engine assumes transition to a 3-cylinder turbocharged engine.	

[319] Heywood 2018, Chapter 6.2.8.

We allow additional downsizing beyond what has been previously modeled because manufacturers have downsized low output naturally aspirated engines to small architecture turbo engines.[320,321,322] We identify low-output naturally aspirated 4-cylinder engines in the analysis fleet that are allowed to downsize to turbocharged 3-cylinder engines, see Chapter 3.1.2. These engines use the costing tabs in the Technologies Input File with the 'L' designation.

Table 3-28 shows the assumed cylinder count and camshaft count used for determining technology costs for each engine architecture. The CAFE Model only uses the assumed cylinder count for determining technology cost, and initial cylinder count is based on the initial analysis fleet assignment, see Chapter 3.1.2. For effectiveness, Autonomie modeling uses engine displacement and power only, and does not directly use cylinder count.

320 Truett, R. 2019. GM Bringing 3-Cylinder Back to North America. Automotive News. Last revised: Dec. 01, 2019. Available at: https://www.autonews.com/cars-concepts/gm-bringing-3-cylinder-back-na. (Accessed: Feb. 8, 2024).
321 Stoklosa, A. 2014. Mini Cooper Hardtop. Car and Driver. Last revised: Dec. 2, 2014. Available at: https://www.caranddriver.com/reviews/a15109143/2014-mini-cooper-hardtop-manual-test-review. (Accessed: Feb. 8, 2024).
322 Leanse, A. 2019. 2020 Ford Escape Options: Hybrid vs. 3-Cylinder EcoBoost vs. 4-Cylinder EcoBoost. Motortrend. Last revised: Sept 24, 2019. Available at: https://www.motortrend.com/news/2020-ford-escape-engine-options-pros-and-cons-comparison. (Accessed: Feb. 9, 2024).

Table 3-28: Assumed Cylinder and Camshaft Count Used for Costing for Each Engine Architecture for Applied Technology

Engine Architecture	Basic Engine (Cyl/Cam)	TURBO0 (Cyl/Cam)	TURBOE (Cyl/Cam)	TURBOD (Cyl/Cam)	TURBO1 (Cyl/Cam)	TURBO2 (Cyl/Cam)	TURBOAD (Cyl/Cam)	ADEACS (Cyl/Cam)	ADEACD (Cyl/Cam)
2C1B_SOHC	2/1	2/2	2/2	2/2	2/2	2/2	2/2	2/1	2/1
2C1B	2/2	2/2	2/2	2/2	2/2	2/2	2/2	2/2	2/2
3C1B_SOHC	3/1	3/2	3/2	3/2	3/2	3/2	3/2	3/1	3/1
3C1B	3/2	3/2	3/2	3/2	3/2	3/2	3/2	3/2	3/2
4C1B_L_SOHC	4/1	3/2	3/2	3/2	3/2	3/2	3/2	4/1	4/1
4C1B_SOHC	4/1	4/2	4/2	4/2	4/2	4/2	4/2	4/1	4/1
4C1B_L	4/2	3/2	3/1	3/1	3/2	3/2	3/1	4/2	4/2
4C1B	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2
4C2B_SOHC	4/2	4/4	4/4	4/4	4/4	4/4	4/4	4/2	4/2
4C2B_L	4/4	3/2	3/2	3/2	3/2	3/2	3/2	4/4	4/4
4C2B	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2
5C1B_SOHC	5/1	4/2	4/2	4/2	4/2	4/2	4/2	5/1	5/1
6C1B_SOHC	6/1	4/2	4/2	4/2	4/2	4/2	4/2	6/1	6/1
6C1B	6/2	4/2	4/2	4/2	4/2	4/2	4/2	6/2	6/2
6C1B_ohv	6/1	4/2	4/2	4/2	4/2	4/2	4/2	6/1	6/1
6C2B_SOHC	6/2	4/2	4/2	4/2	4/2	4/2	4/2	6/2	6/2
6C2B	6/4	4/2	4/2	4/2	4/2	4/2	4/2	6/4	6/4
6C2B_OHV	6/2	4/2	4/2	4/2	4/2	4/2	4/2	6/2	6/2
8C2B_SOHC	8/2	6/2	6/2	6/2	6/2	6/2	6/2	8/2	8/2
8C2B	8/4	6/4	6/4	6/4	6/4	6/4	6/4	8/4	8/4
8C2B_ohv	8/2	6/2	6/2	6/2	6/2	6/2	6/2	8/2	8/2
10C2B_SOHC	10/2	8/2	8/2	8/2	8/2	8/2	8/2	10/2	10/2
10C2B	10/4	8/4	8/4	8/4	8/4	8/4	8/4	10/4	10/4
10C2B_ohv	10/2	8/2	8/2	8/2	8/2	8/2	8/2	10/2	10/2
12C2B_SOHC	12/2							12/2	12/2
12C2B	12/4							12/4	12/4

12C4B_SOHC	12/4							12/4	12/4
12C4B	12/8							12/8	12/8
16C4B_SOHC	16/4							16/4	16/4
16C4B	16/8							16/8	16/8

Table 3-29: Assumed Cylinder and Camshaft Count Used for Costing for Each Engine Architecture for Applied Technology (continued)

Engine Architecture	HCR (Cyl/Cam)	HCRE (Cyl/Cam)	HCRD (Cyl/Cam)	VCR (Cyl/Cam)	VTG (Cyl/Cam)	VTGE (Cyl/Cam)	ADSL (Cyl/Cam)	DSLI (Cam/Cyl)
2C1B_SOHC	2/1	2/1	2/1	2/2	2/2	2/2	2/2	2/2
2C1B	2/2	2/2	2/2	2/2	2/2	2/2	2/2	2/2
3C1B_SOHC	3/1	3/1	3/1	3/2	3/2	3/2	3/2	3/2
3C1B	3/2	3/2	3/2	3/2	3/2	3/2	3/2	3/2
4C1B_L_SOHC	4/1	4/1	4/1	3/2	3/2	3/2	3/2	3/2
4C1B_SOHC	4/1	4/1	4/1	4/2	4/2	4/2	4/2	4/2
4C1B_L	4/2	4/2	4/2	3/1	3/1	3/1	3/1	3/1
4C1B	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2
4C2B_SOHC	4/2	4/2	4/2	4/4	4/4	4/4	4/4	4/4
4C2B_L	4/4	4/4	4/4	3/2	3/2	3/2	3/2	3/2
4C2B	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2
5C1B_SOHC	5/1	5/1	5/1	4/2	4/2	4/2	4/2	4/2
6C1B_SOHC	6/1	6/1	6/1	4/2	4/2	4/2	4/2	4/2
6C1B	6/2	6/2	6/2	4/2	4/2	4/2	4/2	4/2
6C1B_ohv	6/1	6/1	6/1	4/2	4/2	4/2	4/2	4/2
6C2B_SOHC	6/2	6/2	6/2	4/2	4/2	4/2	4/2	4/2
6C2B	6/4	6/4	6/4	4/2	4/2	4/2	4/2	4/2
6C2B_OHV	6/2	6/2	6/2	4/2	4/2	4/2	4/2	4/2
8C2B_SOHC	8/2	8/2	8/2	6/2	6/2	6/2	6/2	6/2
8C2B	8/4	8/4	8/4	6/4	6/4	6/4	6/4	6/4
8C2B_ohv	8/2	8/2	8/2	6/2	6/2	6/2	6/2	6/2

10C2B_SOHC	10/2	10/2	10/2	8/2	8/2	8/2	8/2	8/2
10C2B	10/4	10/4	10/4	8/4	8/4	8/4	8/4	8/4
10C2B_ohv	10/2	10/2	10/2	8/2	8/2	8/2	8/2	8/2
12C2B_SOHC	12/2	12/2	12/2					
12C2B	12/4	12/4	12/4					
12C4B_SOHC	12/4	12/4	12/4					
12C4B	12/8	12/8	12/8					
16C4B_SOHC	16/4	16/4	16/4					
16C4B	16/8	16/8	16/8					

3.1.5.1. Basic Engines

DMCs for basic engine technologies are based on engine cylinder and bank count and configuration. DMC examples are shown in Table 3-30. We sourced these costs from publications and historical cost studies,[323,324] and updated them to 2021 dollars for this analysis. The DMC for each technology is a function of unit cost times either the number of cylinders or number of banks, based on how the technology is applied to the system. The DEAC technology is slightly different in that we do not use unit DMC costs but apply an incremental DMC for the various cylinder count configurations.

Table 3-30: Examples of Basic Engine Technology Incremental DMCs Used for the LD and HDPUV Analysis in 2018 Dollars[325]

Engine Technologies – Direct Manufacturer Costs (2018$) for Basic Engine Technologies								Incremental To
Tech	Basis	Unit DMC	DMC for 4-Cylinder 1-Bank	DMC for 4-Cylinder 2-Bank	DMC for 6-Cylinder 1-Bank	DMC for 6-Cylinder 2-Bank	DMC for 8-Cylinder 2-Bank	
VVL	Cylinder	55.76	223.04	223.04	334.56	334.56	446.08	Base Engine
SGDI	Cylinder	61.68	246.72	246.72	370.08	370.08	493.44	Base Engine
DEAC	-	-	114.72	114.72	135.37	135.37	152.58	Base Engine
ADEACS	Cylinder	48.00	192.00	192.00	288.00	288.00	384.00	SGDI, DEAC
ADEACD	Cylinder	89.59	358.36	358.36	537.54	537.54	716.72	SGDI, DEAC

We apply RPE and learning to the incremental DMCs, see Chapter 2.6. To reach an absolute cost starting point, we sum the basic engine technology costs to establish an overall absolute cost for the technology combinations. For a full listing of all absolute costs, see the LD and HDPUV Technologies Input Files. For the basic engines, to calculate an absolute cost, we assign a base engine cost to the engine, examples are shown in Table 3-31, then add an incremental cost for each basic engine technology, examples are shown in Table 3-32. As an example, a LD 4C1B DOHC engine with VVL and SGDI has an absolute cost of $6,535.50 (5,735.46+330.98+366.06) for model year 2022 but in 2021 dollars. Table 3-33 shows examples of absolute costs for ADEACS and ADEACD engines.

Table 3-31: Examples of Base Absolute Costs for MY 2022 LD Basic Engine Technologies in 2021 Dollars

	4C1B	6C2B	8C2B
SOHC	5478.79	6278.45	6956.80
DOHC	5738.46	6797.79	7476.14
OHV	NA	6367.50	7045.85

Table 3-32: Example Incremental Absolute Costs for Adding LD Basic Engine Technologies for MY 2022 in 2021 Dollars

	4C1B	6C2B	8C2B

323 Kolwich, G. 2015. Diesel Cost Analysis. FEV. P311732-02 at 259.
324 2015 NAS report, at 7.
325 Note that DMCs are in 2018 dollars and the Absolute costs are in 2021 dollars.

VVL	330.98	496.47	661.96
SGDI	366.06	549.08	732.11
DEAC	169.31	199.79	225.19

Table 3-33: Examples of Absolute Costs for ADEACS and ADEACD Technologies for MY 2022 in 2021 Dollars

	4C1B	6C2B	8C2B
ADEACS	6,586.99	8,031.16	9,079.44
ADEACD	6,876.69	8,450.96	9,639.17

***NOTE**: ADEACS and ADEACD costs appear as absolute costs, which includes the engine and technologies costs summed together and shown in the Technologies Input File.

3.1.5.2. Advanced Engines

We determine the costs of the advanced engine technologies by adding the costs of the advanced engine technology to the basic engine technology costs, and then applying the RPE and learning factor based on the year that the technology is applied. The costs for forced induction, Atkinson engines, Miller engines, VCR engines, diesel engines, and alternative fuel engines are discussed below.

3.1.5.2.1. Forced Induction Engines

We calculate the absolute cost for TURBO0 by adding the TURBO0 DMC incremental cost to the basic engine technology costs, apply the RPE, apply the learning effects, and also apply the same rules for cost downsizing discussed above in Chapter 3.1.5. The cost relationship is summarized in Table 3-34 and Table 3-35.

We continue the same methodology for the TURBOE, TURBOD, TURBO1, TURBO2 and TURBOAD technology costs in the same manner as TURBO0. For TURBOE we add the respective incremental costs of cooled EGR to the TURBO0 technology cost. For TURBOD we add the respective incremental costs of DEAC to the TURBO0 technology. For TURBO1 we add the respective incremental costs to TURBO0. For TURBO2 we add the respective incremental costs to TURBO1, and for TURBOAD we add the respective incremental costs of ADEACD to TURBO0. We apply the rules for cost downsizing discussed above, for each forced induction engine technology.

Table 3-34 and Table 3-35 below shows the DMCs for forced induction engines in the light-duty and HDPUV analyses, in 2018 dollars. The TURBOAD technology also includes an incremental cost of $114.72 for 4-cylinder, $135.37 for 6-cylinder, and $152.58 for 8-cylinder engines that is added to the unit DMC cost. Table 3-36 and Table 3-37 shows examples of absolute costs for the LD 4C1B turbo engines,[326] across multiple model years, demonstrating the application of both the RPE and learning rates. Table 3-38 and Table 3-39 show examples absolute costs for the 6C2B turbo engines, across multiple model years, with RPE and learning rates applied. These costs can be found in the LD and HDPUV Technologies Input Files.

Table 3-34: Examples of LD Turbocharged Downsized Engine Incremental DMCs in 2021 Dollars

Engine Technologies – Direct Manufacturer Costs (2021$) for Turbocharged Technologies								Incremental To
Tech	Basis	Unit DMC	DMC for 4-Cylinder 1-Bank Engine	DMC for 4-Cylinder 2-Bank Engine	DMC for 6-Cylinder 1-Bank Engine	DMC for 6-Cylinder 2-Bank Engine	DMC for 8-Cylinder 2-Bank Engine	
TURBO0	None	-	698.71	698.71	585.57	585.57	1069.36	Base Engine

[326] These costs represent the cost for a 6C2B naturally aspirated engine to become a forced induction (turbo) engine, per examples discussed in Table 3-38.

TURBOE	None	-	310.67	310.67	310.67	310.67	310.67	TURBO0
TURBOD	None		123.4	123.4	145.61	145.61	164.12	TURBO0
TURBO1	Cyl	59.98	239.91	940.93	947.77	947.77	1553	TURBO0
TURBO2	None	-	258.74	259.38	259.38	259.38	437.22	TURBO1
TURBOAD	Cyl	96.37	508.86	508.86	723.8	723.8	935.05	TURBO0

Table 3-35: Examples of HDPUV Turbocharged Downsized Engine Incremental DMCs in 2021 Dollars

Engine Technologies – Direct Manufacturer Costs (2021$) For Turbocharged Technologies							Incremental To
Tech	Basis	Unit DMC	DMC for 4-Cylinder 1-Bank Engine	DMC for 6-Cylinder 1-Bank Engine	DMC for 6-Cylinder 2-Bank Engine	DMC for 8-Cylinder 2-Bank Engine	
TURBO0	None	-	634.56	634.56	634.56	634.56	Base Engine

Table 3-36: Examples of LD Absolute Costs Used for I4 Turbocharged Engines in 2021 Dollars (costs include DMCs, RPE, and learning rate factor)

	4C1B Costs (2021$)			
Technology	2020	2022	2026	2030
TURBO0	6,556.22	6,537.93	6,515.33	6,499.76
TURBOE	7,001.43	6,965.00	6,911.14	6,875.22
TURBOD	6,727.75	6,707.24	6,680.83	6,662.11
TURBO1	6,891.54	6,868.91	6,838.86	6,817.13
TURBO2	7,511.95	7,440.48	7,314.21	7,231.49
TURBOAD	7,190.20	7,140.79	7,079.31	7,039.76

Table 3-37: Examples of HDPUV Absolute Costs Used for I4 Turbocharged Engines in 2021 Dollars (costs include DMC, RPE, and learning rate factor)

	4C1B Costs (2021$)				
Technology	2020	2022	2026	2030	2035
TURBO0	6,481.14	6,464.52	6,444.00	6,429.86	6,426.93

Table 3-38: Examples of LD Absolute Costs Used for V6 Turbocharged Engines in 2021 Dollars (costs include DMC, RPE, and learning rate factor)

	6C2B Costs (2021$)			
Technology	2020	2022	2026	2030
TURBO0	7,483.14	7,467.81	7,448.87	7,435.82
TURBOE	7,928.35	7,894.88	7,844.68	7,811.29
TURBOD	7,685.55	7,667.60	7,644.16	7,627.40
TURBO1	7,986.12	7,964.28	7,934.17	7,911.89
TURBO2	8,606.53	8,535.86	8,409.52	8,326.25

TURBOAD	8,434.11	8,372.11	8,294.85	8,245.82

Table 3-39: Examples of HDPUV Absolute Costs Used for V6 Turbocharged Engines in 2021 Dollars (costs include DMC, RPE, and learning rate factor)

	6C2B Costs (2021$)				
Technology	2020	2022	2026	2030	2035
TURBO0	7,540.47	7,523.86	7,503.33	7,489.19	7,486.26

3.1.5.2.2. High Compression Ratio Engines

We use DMCs for HCR engines based on the 2015 NAS analysis, but the cost accounting is aggregated differently than the 2015 NAS report. We include other types of technology present in the engines, like SGDI, and the configuration of the engine, such as SOHC versus DOHC in the cost estimates. Finally, we determine the HCRE and HCRD technology cost by adding the cooled EGR and DEAC costs, respectively, to the HCR engine costs. Examples of the HCR DMC values are shown in Table 3-40.

We then apply an RPE factor and learning curve. Table 3-41 and Table 3-42 show examples of the full absolute costs used for the engine technologies. To see all costs across all model years, please see the LD Technologies Input File.

Table 3-40: Examples of HCR Technology Incremental DMCs in 2021 Dollars

Engine Technologies – Direct Manufacturer Costs (2021$) for HCR Technologies								Incremental To
Tech	Basis	Unit DMC	DMC for 4-Cylinder 1-Bank Engine	DMC for 4-Cylinder 2-Bank Engine	DMC for 6-Cylinder 1-Bank Engine	DMC for 6-Cylinder 2-Bank Engine	DMC for 8-Cylinder 2-Bank Engine	
HCR	none	-	457.55	457.55	457.55	457.55	457.55	Base Engine
HCRE	none	-	310.67	310.64	310.67	310.67	310.67	HCR
HCRD	none	-	123.4	126.62	1221.24	145.61	164.12	HCR

Table 3-41: Examples of Absolute Costs for I4 HCR Engines (costs include DMC, RPE, and learning rate factor) in 2021 Dollars

	4C1B Costs (2021$)			
Technology	2020	2022	2026	2030
HCR	5,979.02	5,937.55	5,894.32	5,873.72
HCRE	6,424.22	6,364.62	6,290.13	6,249.19
HCRD	6,150.55	6,106.86	6,059.82	6,036.07

Table 3-42: Examples of Absolute Costs for V6 HCR Engines (costs include DMC, RPE, and learning rate factor) in 2021 Dollars

	6C2B Costs (2021$)			
Technology	2020	2022	2026	2030
HCR	7,038.35	6,996.88	6,953.65	6,933.05
HCRE	7,483.56	7,423.95	7,349.46	7,308.52

HCRD	7,240.76	7,196.67	7,148.94	7,124.63

3.1.5.2.3. Miller Engines

We use cost data from an FEV technology cost assessment, performed for ICCT, to estimate the DMC for Miller cycle engines with VTG.[327] We considered costs from the 2015 NAS study that referenced a NESCCAF 2004 report,[328] but believe the reference material from the FEV report provides more updated cost estimates for the VTG technology.

Despite not using the 2015 NAS report cost data, we did use the NAS 2015 methodology for aggregating the individual component and system costs to establish a DMC for the Miller cycle engine for each engine configuration. We use a value of $525 (2010$) plus cost of CEGR, minus cost of VVT, VVL, and SGDI for the VTG cost estimate. From the VTG estimate we build a cost for electrically-assisted variable supercharger VTGE (Eng23c) engines based on the 2015 NAS report that uses a cost of $1050 (2010$) plus the cost of the mild hybrid battery. Examples of the DMC for these technologies are shown in Table 3-43. Example costs are shown in Table 3-44 for 4C1B engines and Table 3-45 for 6C2B engines and include application of the RPE and learning factors. Costs for all engine architectures and model years can be seen in the Technologies Input File.

Table 3-43: Examples of Incremental DMCs Used for Miller Cycle Engines (VTG, VTGE) in 2021 Dollars

Engine Technologies - Direct Manufacturer Costs (2021$) for Miller Technologies					**Incremental To**
Tech	DMC for 4-Cylinder 1-Bank Engine	DMC for 6-Cylinder 1-Bank Engine	DMC for 6-Cylinder 2-Bank Engine	DMC for 8-Cylinder 2-Bank Engine	
VTG	664.12	664.12	664.12	664.12	TURBO2
VTGE	1,295.65	1,295.65	1,295.65	1,295.65	VTG

Table 3-44: Examples of Miller Cycle I4 Engines' Absolute Costs Used for VTG and VTGE Technology (costs include DMC, RPE, and learning rate factor) in 2021 Dollars

	4C1B Costs (2021$)			
Technology	2020	2022	2026	2030
VTG	8,463.64	8,353.42	8,160.32	8,034.11
VTGE	10,163.89	9,873.37	9,445.64	9,153.88

Table 3-45: Examples of Miller Cycle V6 Engines' Absolute Costs Used for VTG and VTGE Technologies (costs include DMC, RPE, and learning rate factor) in 2021 Dollars

	6C2B Costs (2021$)			
Technology	2020	2022	2026	2030
VTG	9,558.22	9,448.80	9,255.63	9,128.87
VTGE	11,258.47	10,968.75	10,540.95	10,248.64

[327] Isenstadt A. et al. 2016. Downsized, Boosted Gasoline Engines. Draft. International Council on Clean Transportation. Available at: https://theicct.org/publication/downsized-boosted-gasoline-engines-2/. (Accessed: Feb. 9, 2024).
[328] NESCCAF. 2004. Reducing Greenhouse Gas Emissions from Light-Duty Motor Vehicles. Final Report. Available at https://www.nesccaf.org/documents/rpt040923ghglightduty.pdf. (Accessed: Feb. 9, 2024).

3.1.5.2.4. Variable Compression Ratio Engines

The base DMCs that we use for VCR engines are based on data from the 2015 NAS report.[329] The 2015 NAS cost for VCR in model year 2025 uses a naturally aspirated engine; however, for this analysis we add the cost of CEGR. Table 3-46 shows an example estimated DMC for the VCR technology. Examples of the absolute costs for 4C1B and 6C2B engines, respectively, are in Table 3-47 and Table 3-48.

Table 3-46: Examples of VCR DMCs in 2021 Dollars

Engine Technologies - Direct Manufacturer Costs (2021$)						Incremental To
Tech	Basis	Unit DMC	DMC for 4-Cylinder 1-Bank Engine	DMC for 6-Cylinder 2-Bank Engine	DMC for 8-Cylinder 2-Bank Engine	
VCR	cylinder	184.44	737.75	1106.63	1475.51	TURBO1

Table 3-47: Examples of Absolute VCR Engine Costs for I4 Engine Configuration (costs include DMC, RPE, and learning rate factor) in 2021 Dollars

	4C1B Costs (2021$)			
Technology	2020	2022	2026	2030
VCR	8,118.90	8,036.04	7,930.71	7,862.56

Table 3-48: Examples of Absolute VCR Engine Costs for V6 Engine Configuration (costs include DMC, RPE, and learning rate factor) in 2021 Dollars

	6C2B Costs (2021$)			
Technology	2020	2022	2026	2030
VCR	9,827.16	9,714.97	9,571.95	9,480.02

3.1.5.2.5. Diesel Engines

Diesel engine DMCs are based on the initial engine cost. The basic level diesel engine (ADSL) cost is based on the cost of a modern light-duty diesel engine.[330] The second level of diesel technology (DSLI) includes the cost of incorporating a combination of low pressure and high pressure EGR, reduced parasitic loss, advanced friction reduction, incorporation of highly-integrated exhaust catalyst with low temperature light-off, and closed loop combustion control. In both ADSL and DSLI, the cost includes after-treatment systems to meet the emissions standards for criteria pollutants.[331] Diesel technology costs are shared between the light-duty and heavy-duty vans because we use the same engine as well as the costs. See Chapter 3.1.1.2.6 for more discussion on the light-duty and heavy-duty van diesel technology. heavy-duty pickup ADSL absolute costs are shown in Table 3-52.

Example costs for the light-duty and heavy-duty pick-up and van (HDPUV) diesel technologies are shown in Table 3-49, Table 3-50, and Table 3-51. All ADSL costs are shown in the LD and HDPUV Technologies Input Files.

[329] 2015 NAS report, at 7.
[330] 2015 NAS report, at 104–05.
[331] 2015 NAS report, at 104.

Table 3-49: Examples of Incremental DMCs Used for LD and HDPUV Diesel Engines (ADSL, DSLI) in 2021 Dollars

Engine Technologies - Direct Manufacturer Costs (2021$) for Diesel Technologies					Incremental To
Tech	DMC for 4-Cylinder 1-Bank Engine	DMC for 6-Cylinder 1-Bank Engine	DMC for 6-Cylinder 2-Bank Engine	DMC for 8-Cylinder 2-Bank Engine	
ADSL	3,813.00	3,813.00	3,813.00	3,813.00	Base Engine
DSLI	123.40	145.61	145.61	164.12	ADSL

Table 3-50: Examples of Absolute Diesel Engine Costs for LD and Heavy-Duty Vans I4 Engine Configuration (costs include DMC, RPE, and learning rate factor) in 2021 Dollars

	4C1B Costs (2021$)			
Technology	2020	2022	2026	2030
ADSL	10,601.57	10,431.23	10,295.84	10,216.79
DSLI	10,762.60	10,586.71	10,446.86	10,365.19

Table 3-51: Examples of Absolute Diesel Engine Costs for LD and Heavy-Duty Vans V6 Engine Configuration (costs include DMC, RPE, and learning rate factor) in 2021 Dollars

	6C2B Costs (2021$)			
Technology	2020	2022	2026	2030
ADSL	11,660.90	11,490.56	11,355.18	11,276.13
DSLI	11,850.92	11,674.03	11,533.38	11,451.23

Table 3-52: Examples of Absolute Diesel Engine Costs for Heavy-Duty Pickups I6 Engine Configuration (costs include DMC, RPE, and learning rate factor) in 2021 Dollars

	6C1B Costs (2021$)				
Technology	2020	2022	2026	2030	2035
ADSL	11,376.53	11,197.03	11,054.36	10,971.06	10,947.40
DSLI	11,566.55	11,380.49	11,232.56	11,146.16	11,121.63

3.1.5.2.6. Alternative Fuel Engines

Examples of costs for CNG engine technologies are shown in Table 3-53 and Table 3-54.[332] CNG engine costs across all model years can be found in the LD Technologies Input File.

Table 3-53: Examples of Absolute CNG Engine Costs for I4 Engine Configuration (costs include DMC, RPE, and learning rate factor) in 2021 Dollars

	4C1B Costs (2021$)			
Technologies	2020	2022	2026	2030

[332] 2015 NAS report, at 61.

CNG	12,856.32	12,782.18	12,633.89	12,485.60

Table 3-54: Examples of CNG Engine Costs for V6 Engine Configuration (costs include DMC, RPE, and learning rate factor) in 2021 Dollars

	6C2B Costs (2021$)			
Technologies	2020	2022	2026	2030
CNG	13,915.66	13,841.51	13,693.22	13,544.93

3.2. Transmission Paths

Transmissions transmit torque from the engine to the wheels. Transmissions primarily use two mechanisms to improve fuel efficiency: (1) a wider gear range, which allows the engine to operate longer at higher efficiency speed-load points; and (2) improvements in friction or shifting efficiency (e.g., improved gears, bearings, seals, and other components), which reduce parasitic losses.

For this analysis, we classify all light-duty and HDPUV vehicle TRANS into discrete transmission technology paths. We use the paths to model the most representative characteristics, costs, and performance of the fuel economy-improving transmissions most likely available during the rulemaking timeframe.

The following subchapters discuss how we define the TRANS in the light-duty and HDPUV fleets. The discussion includes the CAFE Model's transmission technology categories, transmission technologies' relative effectiveness, and transmission costs. The following subchapters also provide an overview of how we assign TRANS and transmission adoption features to the light-duty and HDPUV fleets.

3.2.1. Transmission Technologies

In this analysis we only model automatic transmissions (AT). ATs are characterized by automatically selecting and shifting between transmission gears for the driver during vehicle operation. We subdivided light-duty ATs into four subcategories: traditional ATs, dual clutch transmissions (DCT), continuously variable transmissions (CVT and eCVT), and direct drive transmissions (DD). We considered HDPUV transmissions to be either planetary automatics or DDs. These transmissions are further discussed in the subsequent subchapters.

There has been a significant reduction in manual transmissions over the years and they made up less than 1% of the vehicles produced in model year 2021.[333] Due to the trending decline of manual transmissions and their current low production volumes, we have removed manual transmissions from this analysis. All model year 2022 vehicles with manual transmissions are mapped as DCTs and assume the DCT costs in the model year 2022 fleet for the light-duty analysis.

Electronic continuously variable transmissions (eCVT) are also not discussed in detail in this analysis and are not specifically shown in the technology pathways. eCVTs are classified as CVTs, but the eCVT module contains both an electric traction motor and generator coupled to the ICE through a single planetary gear set.[334] eCVTs are considered integral parts of electrified drivetrains (such as power-split hybrids) and are not applied as a standalone technology. See Chapter 3.2.2 for a discussion of how we assign the eCVT in the analysis fleet.

Direct drive transmissions are also not discussed in detail in this analysis and are not specifically shown in the technology pathways. DD transmissions are classified as ATs but have a direct connection between the wheels and a drive motor. In a DD transmission, the ratio between wheel speed and motor speed remains constant. DD transmissions are considered integral parts of electrified drivetrains (such as in BEVs) and are

333 2023 EPA Automotive Trends Report.
334 EPA. 2011. Light Duty Technology Cost Analysis, Power-Split and P2 HEV Case Studies. Technical Report. EPA-420-R-11-015. Assessment and Standards division. Prepared for EPA by FEV, Inc. Available at: https://nepis.epa.gov/Exe/ZyPDF.cgi/P100EG1R.PDF?Dockey=P100EG1R.PDF. (Accessed: Feb. 9, 2024).

not applied as a standalone technology. See Chapter 3.2.2 for a discussion of how we assign the DD transmission in the initial fleet.

We also include the application of high efficiency gearbox (HEG) technology improvements as options to the TRANS (designated as L2 or L3 in our analysis to indicate level of technology improvement). HEG improvements for transmissions represent incremental advancements in technology that improve efficiency, such as reduced friction seals, bearings and clutches, super finishing of gearbox parts, and improved lubrication. These advancements are all aimed at reducing frictional and other parasitic loads in transmissions to improve efficiency. We consider three levels of HEG improvements in this analysis based on the NAS 2015 recommendations, and CBI data.[335] We apply HEG efficiency improvements to ATs and CVTs, as those transmissions inherently have higher friction and parasitic loads related to hydraulic control systems and greater component complexity, compared to DCTs. Manufacturers were developing AT7, AT9, and AT10 transmissions during the same time period as the AT8 with HEG technology improvements and it was assumed these new transmissions would include the same HEG technology improvements. For this analysis the AT7, AT9, and AT10 transmissions are assigned HEG technology and are shown as AT7L2, AT9L, and AT10L2. We identify transmissions for the light-duty and HDPUV analyses by technology type, gear count, and HEG technology level using the naming conventions shown in Table 3-55, below.

Table 3-55: Naming Conventions Used for Transmission Technology Pathways

Transmission	Name
5-speed automatic	AT5
6-speed automatic	AT6
7-speed automatic level 2 HEG	AT7L2
8-speed automatic	AT8
8-speed automatic level 2 HEG	AT8L2
8-speed automatic level 3 HEG	AT8L3
9-speed automatic level 2 HEG	AT9L2
10-speed automatic level 2 HEG	AT10L2
10-speed automatic level 3 HEG	AT10L3
6-speed dual-clutch	DCT6
8-speed dual-clutch	DCT8
Continuous variable transmission	CVT
Continuous variable transmission level 2 HEG	CVTL2

3.2.1.1. Traditional Automatic Transmissions

Conventional planetary gear ATs are the most popular transmission.[336] ATs typically contain three or four planetary gear sets that provide the various gear ratios. Gear ratios are selected by activating solenoids that engage or release multiple clutches and brakes as needed. We include ATs with gear counts ranging from five speeds to ten speeds in both the light-duty and HDPUV analyses, see Figure 3-13 and Figure 3-14.[337]

ATs are traditionally packaged with torque converters, which provide a fluid coupling between the engine and the driveline and provide a significant increase in launch torque. When transmitting torque through this fluid coupling, energy is lost due to the churning fluid. These losses can be eliminated by engaging the torque converter clutch to directly connect the engine and transmission ("lockup").

[335] 2015 NAS Report, at 191.
[336] 2023 EPA Automotive Trends Report.
[337] Specifically, we considered five-speed automatic transmissions (AT5), six-speed automatic transmissions (AT6), seven-speed automatic transmission (AT7), eight-speed automatic transmissions (AT8), nine-speed automatic transmissions (AT9), and ten-speed automatic transmissions (AT10).

In general, ATs with a greater number of forward gears and with larger overall ratio spread offer more potential for fuel consumption reduction, but at the expense of larger packaging, added weight and increased costs. Transmissions with a higher number of gears typically offer a wider overall speed ratio and more opportunity to operate the engine near its most efficient point. For the Draft TAR and 2020 final rule, we and EPA surveyed ATs in the market to assess trends in gear count and purported fuel economy improvements.[338] Based on that survey, and also EPA's more recent Automotive Trends Reports,[339] we model ATs with a range of 5 to 10 gears with three levels of HEG technology.

The benefits and popularity of ATs are also true for HDPUVs, where ATs are the only technology in the pathway aside from DD. There are several reasons ATs are the only transmission for the HDPUV analysis. First, with the exception of DD transmissions, all of the vehicles in the HDPUV analysis fleet use ATs.[340] Second, from an engineering standpoint, DCTs and CVTs are not suited for the work requirements of HDPUVs, as discussed in Chapter 3.2.3.2 and Chapter 3.2.3.3.

The HDPUV ATs work in the same way as the light-duty ATs and are labeled the same, but they are sized and mapped[341] to account for the additional work, durability, and payload these vehicles are designed to conduct. The HDPUV transmissions are sized with larger clutch packs, higher hydraulic line pressures, different shift schedules, larger torque converter and different lock up logic, and stronger components when compared to their light-duty counterparts.

3.2.1.2. Continuously Variable Transmissions

Conventional CVTs consist of two cone-shaped pulleys, connected with a belt or chain. Moving the pulley halves allows the belt to ride inward or outward radially on each pulley, effectively changing the speed ratio between the pulleys. This ratio change is smooth and continuous, unlike the step changes of other transmission varieties.[342]

One advantage of CVTs is that they continue to transmit torque during ratio changes. In ATs and some DCTs, energy from the engine is wasted during a ratio change or shift. ATs and some DCTs have a delay during shifts caused by the torque disruption during gear changes. Another advantage of a CVT is that with its effectively "infinite" number of gear steps, within its ratio range it can maintain engine operation closer to the maximum efficiency for the required power. In contrast, ATs efficiency peaks with 9 to 10 gears,[343,344] and approaches the CVT's ability to operate the engine at the most efficient operating point. While a CVT can improve fuel economy over ATs with fewer gears, it typically provides minimal improvement over 9- and 10-speed ATs.

One disadvantage of CVTs is that they transmit torque from the engine to the wheels through friction alone and do not rely on gears like planetary automatics or DCTs. As engine torque increases, a larger clamping force must be applied between the cones and belt or chain to prevent slipping, which results in higher parasitic losses.[345] CVTs still have lower torque capacities than other types of transmissions and therefore, are not suitable for high torque applications that come with larger engines and higher towing needs.[346] Due to the current limited torque capacity of CVTs, this technology doesn't appear in high torque or high load applications in the light-duty or HDPUV fleets.

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[338] EPA. 2023. Regulatory Impact Analyses for Air Pollution Regulations. Last revised: May 19, 2023. Available at: https://www.epa.gov/ecoNomic-and-cost-analysis-air-pollution-regulations/regulatory-impact-analyses-air-pollution. (Accessed: Feb. 9, 2024).
[339] 2023 EPA Automotive Trends Report.
[340] Market Data Input File.
[341] ANL - All Assumptions_Summary_NPRM_2206.xlsx; ANL - Data Dictionary_NPRM_2206.xlsx; ANL - Summary of Main Component Performance, Assumptions_NPRM_2206.xlsx; ANL – All Assumptions Summary – (2b-3) FY22 NHTSA – 220811.xlsx; ANL – Data Dictionary – (2b-3) FY22 NHTSA – 2200811.xlsx; ANL – Summary of Main Component Performance Assumptions – (2b-3) FY22 NHTSA – 220811.xlsx.
[342] 2015 NAS report, at 171.
[343] Robinette, D.,Wehrwein, D. 2015. Automatic Transmission Technology Selection Using Energy Analysis. *CTI Symposium - Automatic Transmissions, HEV and EV Drives*. Vol. 9: Novi, MI. Available at: https://www.researchgate.net/publication/277328952_Automatic_Transmission_Technology_Selection_Using_Energy_Analysis. (Accessed: Feb. 9, 2024).
[344] Greimel, H. 2014. ZF CEO: We're Not Chasing 10-Speeds. Automotive News. Last revised: Nov. 23, 2014. Available at http://www.autonews.com/article/20141123/OEM10/311249990/zf-ceo:-were-not-chasing-10-speeds. (Accessed: Feb. 9, 2024).
[345] 2015 NAS report, at 183.
[346] 2015 NAS report, at 264.

We model two types of CVT systems in the light-duty analysis, the basic level CVT and a CVT with HEG technology applied, see Figure 3-13. As discussed above, eCVTs are not modeled as a standalone technology but are incorporated in SHEVPS.

3.2.1.3. Dual Clutch Transmissions

DCTs, like ATs, automate shift and launch functions. DCTs use separate clutches for even-numbered and odd-numbered gears, allowing the next gear needed to be pre-selected, resulting in faster shifting. The use of multiple clutches in place of a torque converter results in lower parasitic losses than ATs. As discussed in Chapter 3.2.1, manual transmissions are not modeled in this analysis and any light-duty vehicles with manual transmission are mapped to DCTs.

However, DCTs have limited penetration in the fleet.[347] DCTs have encountered issues with customer acceptance.[348] The NAS also stated in its 2021 report, "... attempts by some automakers to introduce this technology to the U.S. market were met with significant customer acceptance issues; for instance, customers accustomed to a torque convertor based AT performance seem to have concerns with a start-up clutch, mostly at lower speeds. Therefore, some automakers have since transitioned away from DCTs, and other automakers scrapped introduction plans prior to launch."[349]

Generally, DCTs are very cost-effective technologies in the simulation, but consumer acceptance issues limit their appeal in the American market. Because of the limited appeal, we constrain application of additional DCT technology to vehicles already using DCT technology, and only model two types of DCTs in the analysis, see Figure 3-13 and Figure 3-14.

3.2.2. Assigning Transmission Technologies in the Analysis Fleet

To understand manufacturers' potential pathways for compliance and the feasibility of different potential stringencies, it is important to first understand the initial state of technology in their fleets. The analysis fleet provides a snapshot of the light-duty and HDPUV U.S. vehicle market for a given model year or model years. It includes transmission assignments for each vehicle and the degree of transmission sharing among those vehicles. Assignments map the transmissions modeled in Autonomie to the real-world transmissions they best represent in terms of configuration, cost, and effectiveness.

3.2.2.1. Transmission Characteristics Considered in Analysis Fleet Assignments

"Assignment" refers to the process of identifying which Autonomie transmission model is most like a vehicle's real-world transmission, taking into account the transmission's configuration and costs. Table 3-56 and Table 3-57 list the Autonomie transmission models and their acronyms that we use in the CAFE Model Input File for the light-duty and HDPUV analyses. For convenience, we refer to these technologies by their acronyms in this subchapter.

We classify the wide variety of transmissions in both the light-duty and HDPUV market into discrete transmission technology paths. We use the paths to model the most representative characteristics, costs, and relative improvements gained from fuel economy-improving technologies from the assigned basic level technology. Due to uncertainty regarding the costs and capabilities of emerging transmission technologies, this analysis only considers TRANS likely to be available during the rulemaking timeframe.

To assess the feasibility of different stringencies, it is important to accurately establish the initial technology content of the fleet. Underestimating the amount of technology in the analysis fleet would lead to overestimating the actual technology application needed for manufacturers to comply with standards and cause the analysis to incorrectly apply technologies that are already present on existing vehicles. Conversely, overestimating the technology present in the analysis fleet would artificially (and incorrectly) limit the technologies manufacturers might apply to meet standards.

[347] 2020 EPA Automotive Trends Report, at 57.
[348] See 2015 NAS report, at 170-1.
[349] 2021 NAS report.

Manufacturer mid-model year CAFE compliance submissions and publicly available manufacturer specification sheets serve as the basis for initial transmission assignments. We use this data to assign transmissions in the analysis fleet and determine which platforms share transmissions. Common transmissions and how we characterize them are discussed in Chapter 3.2.3.

Table 3-56: LD Transmission Technologies

Transmission	Name
5-speed automatic	AT5
6-speed automatic	AT6
7-speed automatic level 2 HEG	AT7L2
8-speed automatic	AT8
8-speed automatic level 2 HEG	AT8L2
8-speed automatic level 3 HEG	AT8L3
9-speed automatic level 2 HEG	AT9L2
10-speed automatic level 2 HEG	AT10L2
10-speed automatic level 3 HEG	AT10L3
6-speed dual-clutch	DCT6
8-speed dual-clutch	DCT8
Continuously variable transmission	CVT
Continuously variable transmission level 2 HEG	CVTL2
Direct drive	DD

Table 3-57: HDPUV Transmission Technologies

Transmission	Name
5-speed automatic	AT5
6-speed automatic	AT6
8-speed automatic	AT8
9-speed automatic level 2 HEG	AT9L2
10-speed automatic level 2 HEG	AT10L2
Direct drive	DD

We specify transmission type, number of gears, and high-efficiency gearbox (HEG) level for the light-duty and HDPUV initial fleet assignments. Transmission types in the light-duty analysis include automatics, direct drive, dual-clutch, and continuously variable, while the HDPUV analysis includes automatics and direct drive, as described in Chapter 3.2.1. HEG levels represent incremental improvements in transmission technology that improve efficiency for automatic and continuously variable transmissions. See Chapter 3.2.1 for further discussion of HEG levels.

The number of gears in the assignments for DCTs usually match the number of gears listed by the data sources, with some exceptions (we assign dual-clutch transmissions with seven and nine gears to DCT6 and DCT8 respectively). We did not model manual transmissions in Autonomie due to their rarity. We assign any initial fleet vehicles with a five or six-speed manual transmission as DCT6, and seven-speed manual transmissions get assigned as DCT8.

For ATs and CVTs, identifying the most appropriate transmission path model requires additional steps; this is because identifying HEG level from specification sheets alone is not always straightforward. We review the age of the transmission design, relative performance versus previous designs, and technologies incorporated to assign an HEG level.

There are no HEG Level 3 ATs in either the MY2022 light-duty or the HDPUV initial analysis fleets. However, for the light-duty analysis we found all 7-speed, all 9-speed, all 10-speed, and some 8-speed AT to be advanced transmissions operating at HEG Level 2 equivalence, see Chapter 3.2.1. Eight-speed AT and CVTs newly introduced in model year 2016 and later are assigned HEG Level 2 for the light-duty fleet. All other transmissions are assigned to their respective transmission's initial level. The (HEG level 1) technologies available include AT6, AT8, and CVT.

We assign vehicles in either the light-duty or HDPUV analyses fleets with a fully electric powertrain a DD transmission. We assign any vehicle in the light-duty analysis fleet with a SHEVPS powertrain an eCVT. These designations are for informational purposes only. If specified, the transmission will not be individually replaced or updated by the model because of the integrated nature of these transmissions. For further discussion of how the model handles transmissions on electrified vehicles, see Chapter 3.2.1.

Table 3-58 and Table 3-59 shows the prevalence of each transmission technology as assigned in the light-duty and HDPUV analysis fleets.

Table 3-58: Penetration Rates of Transmission Technologies in the MY 2022 LD Analysis Fleet

Transmission Technology	Sales Volume	Penetration Rate
AT5	141,306	0.98%
AT6	913,909	6.36%
AT7L2	25,239	0.36%
AT8	3,506,949	24.39%
AT8L2	651,315	4.53%
AT8L3	-	0%
AT9L2	1,547,989	10.76%
AT10L2	1,770,784	12.31%
AT10L3	-	0%
DCT6	370,163	2.57%
DCT8	195,517	1.36%
CVT	1,728,421	12.02%
CVTL2	1,519,312	10.56%
DD (Total BEV)	744,489	5.18%
eCVT (Total HEV and PHEV)	1,234,079	8.61%
Total Automatic	8,584,491	59.69%
Total Dual-Clutch	565,680	3.93%
Total Continuously Variable	3,247,733	22.58%

Table 3-59: Penetration Rates of Transmission Technologies in the HDPUV Analysis Fleet

Transmission Technology	Sales Volume	Penetration Rate
AT5	21,092	2.41%
AT6	713,733	81.39%
AT8	85,777	9.78%
AT9L2	977	0.11%

AT10L2	830	0.09%
DD	54,508	6.22%
Total Automatic	822,409	93.78%

3.2.2.2. Other Transmission Characteristics Recorded and Used to Identify Common Transmissions

Manufacturers often use transmissions that are the same or similar on multiple vehicles. To reflect this, we consider shared transmissions for manufacturers as appropriate. For more information, see Chapter 2.2.1.6.

In addition to technology type, gear count, and HEG level, we characterize transmissions in the analysis fleet by drive type and vehicle architecture. We consider front-, rear-, all-, and four-wheel drive in the analysis. The definition of drive types in the analysis does not always align with manufacturers' drive type designations; see the end of this subchapter for further discussion. These characteristics, supplemented by information such as gear ratios and production locations, show that manufacturers use transmissions that are the same or similar on multiple vehicle models. Manufacturers have told us they do this to control component complexity and associated costs for development, manufacturing, assembly, and service. If multiple vehicle models share technology type, gear count, drive configuration, internal gear ratios, and production location, the transmissions are treated as a single group for the analysis. Vehicles in the light-duty and HDPUV analysis fleets with the same transmission configuration adopt additional fuel-saving transmission technology together, as described in Chapter 2.2.1.6. It is important to note that transmission sharing does not occur between the light-duty and HDPUV fleets. The HDPUV fleet is primarily focused on work vehicles that are carrying additional cargo, higher gross vehicle weight ratings, higher towing capacities, and more stop and go activities. This results in HDPUV transmissions typically having a more robust build, lower gearing, and tailored transmission tuning when compared to light-duty transmissions.[350,351]

We designate and track common transmissions in the Market Data Input File using transmission codes. Transmission codes are six-digit numbers that are assigned to each transmission and encode information about them. This information includes the manufacturer, drive configuration, transmission type, and number of gears. This process is the same for the light-duty and HDPUV analyses even though we do not allow transmission sharing between the light-duty and HDPUV fleets. Table 3-60 lists the possible values for each digit in the transmission code and its meaning.

[350] 2021 Ford Super Duty Pickup Technical Specifications.
[351] 2021 Ford F-150 Technical Specifications.

Table 3-60: Transmission Codes Guide

Transmission Code Digit	Meaning	Values	Notes
First and Second	Manufacturer	11 - General Motors 12 - Stellantis 13 - Ford 14 - Tesla 15 - Karma 16 - Rivian 17 - Lucid 21 - Honda 22 - Nissan 23 - Toyota 24 - Mazda 25 - Mitsubishi 26 - Subaru 31 - Hyundai 32 - Kia 41 - BMW 42 - Volkswagen 43 - Daimler 44 - Jaguar-Land Rover 45 - Volvo	First digit indicates manufacturer heritage region: 1 - USA 2 - Japan 3 - South Korea 4 - Europe
Third	Drive Configuration	1 - Front-Wheel Drive 2 - All-Wheel Drive 3 - Rear-Wheel Drive 4 - Four-Wheel Drive	Drive configuration determined by vehicle architecture
Fourth	Transmission Type	2 - Automatic 3 - Continuously Variable 4 - Dual-Clutch	
Fifth	Number of Gears	0 - 10-speed 1 - Continuously variable 5 - 5-speed 6 - 6-speed 7 - 7-speed 8 - 8-speed 9 - 9-speed	
Sixth	Transmission Variant	1 through 9	

An example of a transmission code is 132281, which corresponds to the Ford Escape's AWD, 8-speed AT. Transmission codes can be decoded by reading the code from left to right: "13" is the manufacturer code for Ford, "2" indicates an AWD vehicle, "2" indicates an AT, "8" indicates eight speeds, and "1" means this is the first variant of this particular transmission.

We assign different transmission codes to variants of a transmission that may appear to be similar based on the characteristics considered in the analysis but are not mechanically identical. We distinguish among transmission variants by comparing their internal gear ratios and production locations. For example, multiple Ford nameplates carry a rear-wheel drive (RWD), 10-speed automatic transmission (AT10) such as the F-150 and the Mustang. Because the F-150 is a pickup truck, it has different needs from its transmission than its sports car counterpart the Mustang, so the analysis assigns different transmission codes to these different nameplates. Because the nameplates have different transmission codes, they are not treated as "shared" for the purposes of analysis in the CAFE Model and can adopt TRANS independently. This is true in both the light-duty and HDPUV analyses.

Note that when determining the drive type of a transmission, the assignment of AWD versus four-wheel drive is determined by vehicle architecture. This assignment does not necessarily match the drive type used by the manufacturer in specification sheets and marketing materials because of inconsistencies in terminology. Vehicles in the light-duty and HDPUV fleets with a powertrain capable of providing power to all wheels and a transverse engine (front-wheel drive architecture) are assigned AWD. Vehicles with power to all four wheels and a longitudinal engine (RWD architecture) are assigned four-wheel drive. An example of where we may deviate from what may be found in marketing material or specifications is the Mercedes Benz E350 4MATIC. The E350 4MATIC is equipped with an AWD system but with a longitudinal engine and powertrain configuration so it is assigned a drive type of four-wheel drive.

3.2.3. Transmission Adoption Features

When evaluating TRANS to improve fuel economy, the CAFE Model considers current transmission architecture. If a manufacturer has already committed to advanced automatic, continuously variable, or dual-clutch transmissions on a vehicle, the CAFE Model will consider higher-tier fuel-saving technologies along the current path. Transmission level technology pathways for the light-duty and HDPUV analyses are illustrated in Figure 3-13 and Figure 3-14 below.[352] The greyed AT5, AT7L2, and CVT nodes are only used as a starting point when we initially assign the technologies to establish the light-duty and HDPUV analysis fleets.

Technology pathways are designed to prevent "branch hopping" – changes in transmission type that would correspond to significant changes in transmission architecture – for vehicles that are relatively advanced on a given pathway. For example, any AT with more than five gears cannot move to a dual-clutch transmission. For a more detailed discussion of path logic applied in the analysis, including technology supersession logic and technology mutual exclusivity logic, please see CAFE Model Documentation S4.5 Technology Constraints (Supersession and Mutual Exclusivity).[353] Additionally, the CAFE Model prevents "branch hopping" to prevent stranded capital associated with moving from one transmission architecture to another. Stranded capital is discussed in more detail in Chapter 2.6.

[352] Technologies that can only be assigned in the baseline fleet include AT5, AT7L2, and CVT; they are indicated by the grey boxes.
[353] NHTSA. 2022. CAFE Compliance and Effects Modeling System. Last Revised: 2022. Available at: https://www.nhtsa.gov/corporate-average-fuel-ecoNomy/compliance-and-effects-modeling-system. (Accessed: Feb. 9, 2024).

Figure 3-13: LD Transmission-Level Technology Pathways

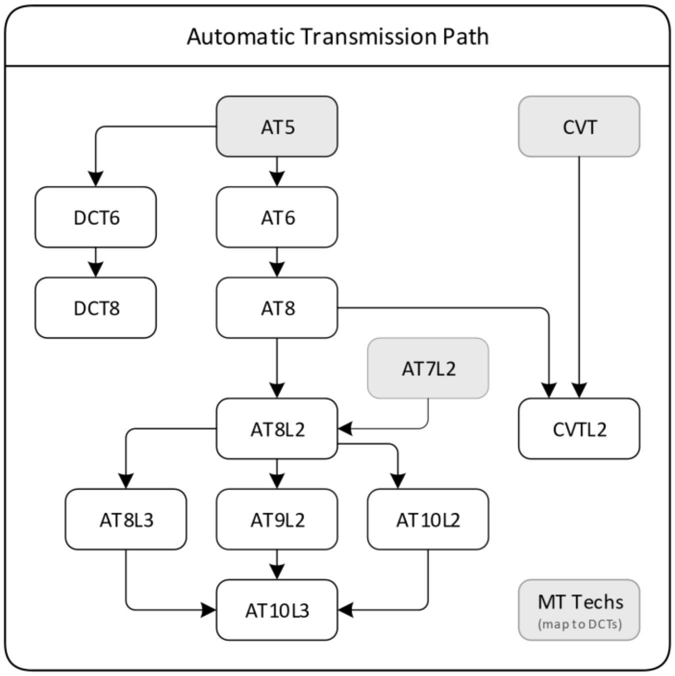
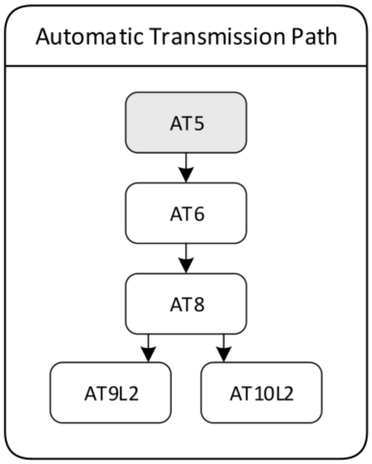


Figure 3-14: HDPUV Transmission-Level Technology Pathways



Some technologies that we model in the analysis are not yet in production, and therefore are not assigned in the initial fleet. Nonetheless, these technologies, which we project will be available in the analysis timeframe, are available for future adoption. For instance, we do not observe any AT10L3s in the initial fleet, but it is plausible that manufacturers that employ 10-speed automatic transmission, Level 2 (AT10L2) technology may improve the efficiency of those AT10L2s in the rulemaking timeframe.

Note that when electrification technologies are adopted, the transmissions associated with those technologies will supersede the existing transmission on a vehicle. The transmission technology is superseded if the model applies strong hybrid, plug-in hybrid, or BEV technologies. For more information, see Chapter 3.3.3.

The following subchapters discuss specific adoption features applied to each type of transmission technology.

3.2.3.1. Automatic Transmissions

For the light-duty analysis, the AT path precludes adoption of other transmission types once a platform progresses past an AT8. We use this restriction to avoid the significant level of stranded capital loss that could result from adopting a completely different transmission type shortly after adopting an advanced transmission, which would occur if a different transmission type were adopted after AT8 in the rulemaking timeframe.

Vehicles that did not start out with AT7L2 transmissions cannot adopt that technology in the model. It is likely that other vehicles will not adopt the AT7L2 technology, as vehicles that have moved to more advanced AT have overwhelmingly moved to 8-speed and 10-speed transmissions.[354]

There are a small number of Mercedes-Benz transmissions in the analysis fleet that use a multiple-disc wet clutch unit in place of a traditional torque converter for their planetary AT. In these few cases, the transmissions were assigned as ATs with their appropriate gear count and a HEG Level 2.

The AT path for HDPUVs is similar to that of the light-duty vehicles, though with fewer options. This is representative of the smaller HDPUV fleet size compared to the light-duty fleet, the types of automatics being used in the current fleet, and the types of automatics manufacturers may use during this rule making period. For more discussion see Chapter 3.2.1.1.

3.2.3.2. Continuously Variable Transmissions

Continuously variable transmission (CVT) adoption is limited by technology path logic and is only available in the light-duty fleet analysis and therefore, not in the technology path for the HDPUV analysis. Vehicles that do not originate with a CVT or vehicles with multispeed transmissions beyond AT8 in the model year 2022 analysis fleet cannot adopt CVTs. Vehicles with multispeed transmissions greater than AT8 demonstrate increased ability to operate the engine at a highly efficient speed and load. Once on the CVT path, the platform is only allowed to apply improved CVT technologies. Due to the limitations of current CVTs discussed in Chapter 3.2.1.2, this analysis restricts the application of CVT technology on light-duty vehicles with greater than 300 lb.-ft of engine torque. This is because of the higher torque (load) demands of those vehicles and CVT torque limitations based on durability constraints. We believe the 300 lb.-ft restriction represents an increase over current levels of torque capacity that is likely to be achieved during the rule making timeframe. This restriction aligns with CVT application in the analysis fleet, in that CVTs are only witnessed on vehicles with under 280 lb.-ft of torque.[355] Additionally, this restriction is used to avoid stranded capital.

3.2.3.3. Dual-Clutch Transmissions

The analysis allows vehicles in the analysis fleet that have DCTs to apply an improved DCT and allows vehicles with an AT5 to consider DCTs. Drivability and durability issues with some DCTs have resulted in a low relative adoption rate over the last decade. This is also broadly consistent with manufacturers' technology choices.[356] DCTs are not a selectable technology for the HDPUV analysis.

3.2.4. Transmission Effectiveness

We use the Autonomie full vehicle simulation tool to understand how transmissions work within the full vehicle system to improve fuel economy, and how changes to the transmission subsystem influence the performance of the full vehicle system. The full vehicle simulation approach clearly defines the contribution of individual TRANS and separates those contributions from other technologies in the full vehicle system. The modeling approach follows the recommendations of the NAS in its 2015 light-duty vehicle fuel economy technology report to use full vehicle modeling supported by application of collected improvements at the sub-model level.[357]

The Autonomie tool models transmissions as a sequence of mechanical torque gains. The torque and speed are multiplied and divided, respectively, by the current ratio for the selected operating condition. Furthermore, torque losses corresponding to the torque/speed operating point are subtracted from the torque input. Torque losses are defined based on a three-dimensional efficiency lookup table that has the following inputs: input

[354] 2023 EPA Automotive Trends Report, at 71, Figure 4.24.
[355] Market Data Input File.
[356] 2023 EPA Automotive Trends Report, at 71, Figure 4.24.
[357] 2015 NAS report, at 292.

shaft rotational speed, input shaft torque, and operating condition. A detailed discussion of the Autonomie transmission modeling can be found in the CAFE Analysis Autonomie Documentation.[358]

We populate transmission template models in Autonomie with characteristics data to model specific transmissions.[359] Characteristics data are typically tabulated data for transmission gear ratios, maps for transmission efficiency, and maps for torque converter performance, as applicable. Different transmission types require different quantities of data. The characteristics data for these models come from peer-reviewed sources, transmission and vehicle testing programs, results from simulating current and future transmission configurations, and confidential data obtained from OEMs and suppliers.[360]

For example, the 10-speed automatic transmission (AT10L2) efficiency curve uses data from South-West Research Institute (SWRI) for the 2017 Ford F-150 10R80 transmission.[361,362] The 10R80 transmission is a 10-speed, rear-wheel-drive transmission that Ford is currently using in both cars and trucks, including the Ford F-150, Ford Mustang, Ford Expedition, Lincoln Navigator, and Ford Ranger.[363] Since this transmission is used in both cars and trucks, the SWRI data for this transmission are applicable to multiple vehicle classes.

We model HEG improvements by modeling improvements to the efficiency map of the transmission. As an example, the initial AT8 model data comes from a transmission characterization study.[364] The AT8L2 has the same gear ratios as the AT8, however, we improve the gear efficiency map to represent application of the HEG level 2 technologies. The AT8L3 models the application of HEG level 3 technologies using the same principle, further improving the gear efficiency map over the AT8L2 improvements.

We comprehensively simulate 15 TRANS for the light-duty analysis and 6 for the HDPUV analysis using the Autonomie tool. Each transmission is modeled with defined gear ratios, gear efficiencies, gear spans, and unique shift logic for the configuration. Chapter 2.3.4.1 discusses specific shift logic employed in the Autonomie modeling. The effectiveness values for the transmission technologies, for all light-duty and HDPUV vehicle technology classes, are shown in Figure 3-15 and Figure 3-16 respectively. Each of the effectiveness values shown is representative of the percentage improvements seen for upgrading only the listed transmission technology for a given combination of other technologies. In other words, the range of effectiveness values seen for each specific technology, e.g., AT10L3, represents the addition of the AT10L3 technology to every technology combination that could add AT10L3. We emphasize that the graph shows the change in fuel consumption values between entire technology keys,[365] and not the individual technology effectiveness values. Using the change between whole technology keys captures the complementary or non-complementary interactions among technologies.

Note that the effectiveness for the AT5, eCVT, and DD technologies is not shown. The DD and eCVT transmissions do not have a standalone effectiveness because those technologies are only implemented as part of electrified powertrains. The AT5 has no effectiveness values because it is a basic level technology against which all other TRANS are compared.

358 Chapter “Autonomie” and Chapter “Vehicle and Component Assumption” of the CAFE Analysis Autonomie Documentation.
359 See the following files which can be found in the rulemaking docket by filtering for Supporting & Related Materials: ANL - All Assumptions_Summary_NPRM_2206.xlsx; ANL - Data Dictionary_NPRM_2206.xlsx; ANL - Summary of Main Component Performance, Assumptions_NPRM_2206.xlsx; ANL – All Assumptions Summary – (2b-3) FY22 NHTSA – 220811.xlsx; ANL – Data Dictionary – (2b-3) FY22 NHTSA – 2200811.xlsx; ANL – Summary of Main Component Performance Assumptions – (2b-3) FY22 NHTSA – 220811.xlsx.
360 Argonne National Laboratory. Downloadable Dynamometer Database. Energy Systems Division. Available at: https://www.anl.gov/taps/downloadable-dynamometer-database. (Accessed:Feb. 9, 2024); Kim, N. et al. 2014. Advanced Automatic Transmission Model Validation Using Dynamometer Test Data. SAE 2014-01-1778. *SAE World Congress*: Detroit, MI. Available at: https://www.sae.org/publications/technical-papers/content/2014-01-1778/. (Accessed:Feb. 9, 2024); Kim, N. et al. 2014. Development of a Model of the Dual Clutch Transmission in Autonomie and Validation with Dynamometer Test Data. *International Journal of Automotive Technologies*. Vol. 15(2): pp 263–71. Available at: https://link.springer.com/article/10.1007/s12239-014-0027-5. (Accessed:Feb. 9, 2024).
361 Chapter “Transmission Assumptions“ of the CAFE Analysis Autonomie Documentation.
362 Wileman, C. 2021. Light-duty Vehicle Transmission Benchmarking, 2017 Ford F-150 with 10R80 and 2018 Honda Accord with Earth Dreams CVT. Report No. DOT HS 813 163. National Highway Traffic Safety Administration.
363 Gears Magazine. 2020. The More You Know About The 10R80…The Better Off You Are! Last revised: Sept. 1, 2020. Available at: https://gearsmagazine.com/magazine/the-more-you-know-about-the-10r80-the-better-off-you-are. (Accessed: Feb. 9, 2024).
364 CAFE Analysis Autonomie Documentation, Chapter titled “Transmission Assumptions”.
365 Technology key is the unique collection of technologies that constitutes a specific vehicle, see Chapter 2.3.6.

Figure 3-15: Light-Duty Transmission Technology Effectiveness Values for All Vehicle Technology Classes (Unconstrained)

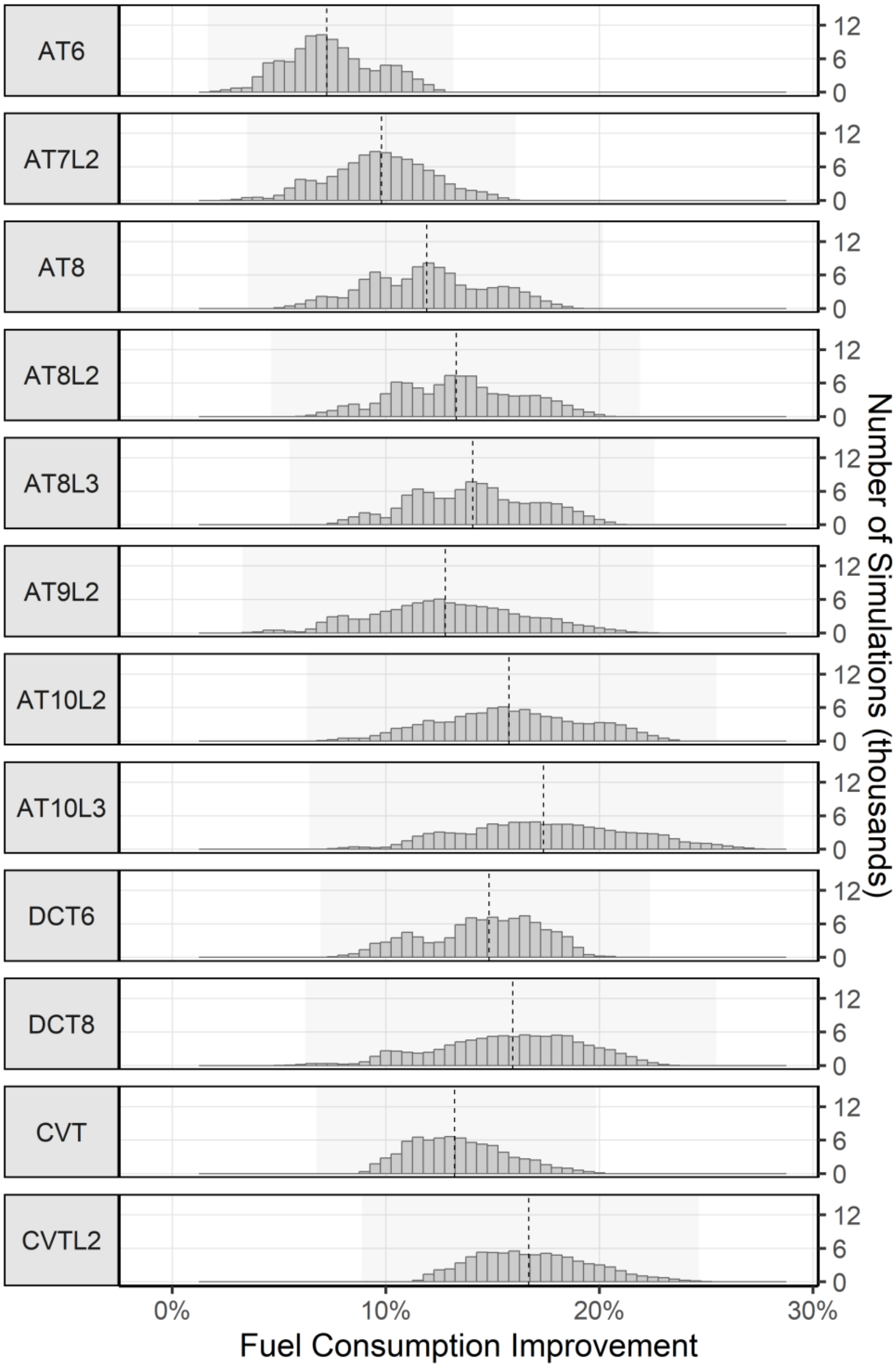


Figure 3-16: Light-Duty Transmission Technology Effectiveness Values for All Vehicle Technology Classes (Standard Setting)

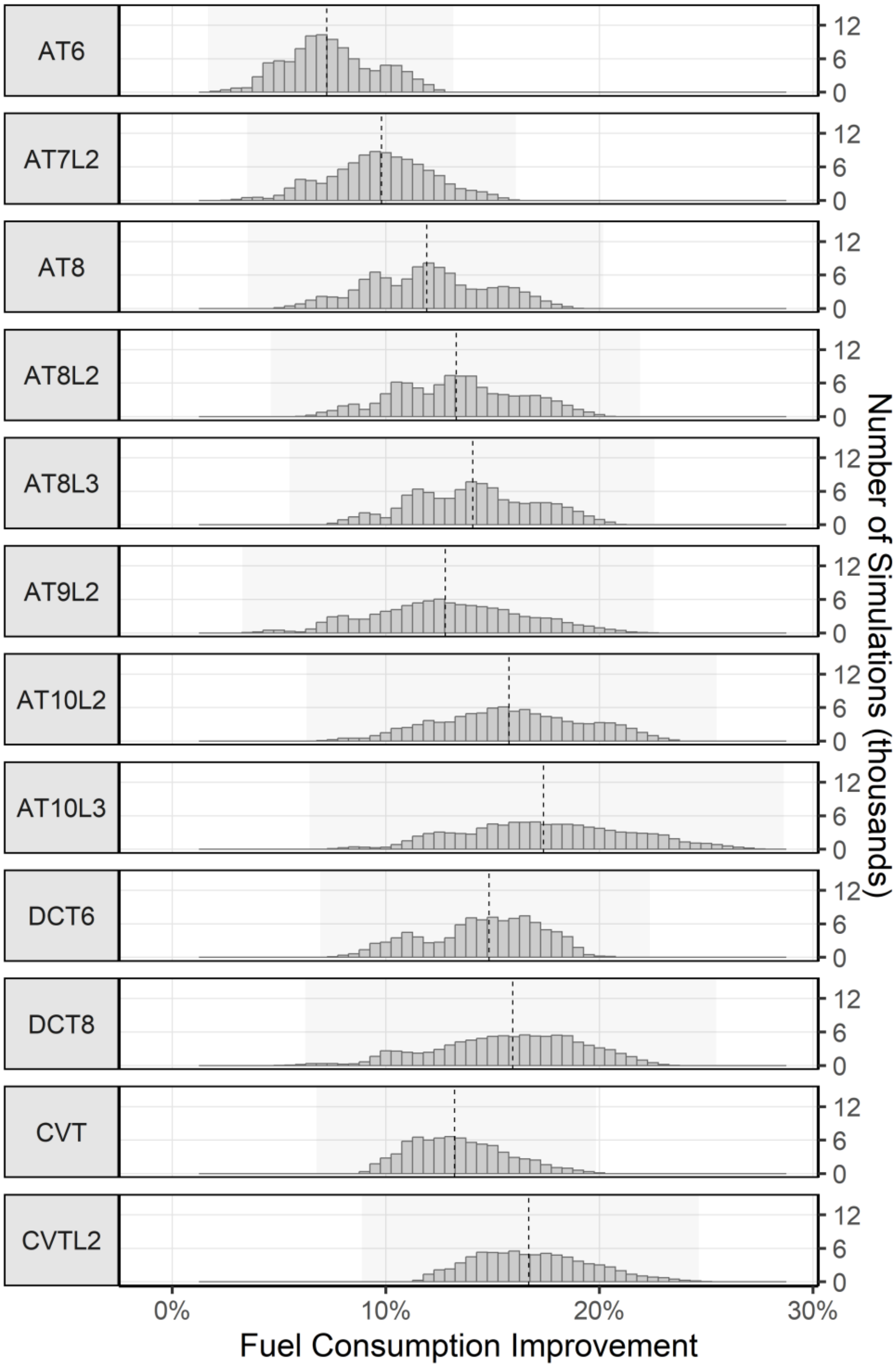
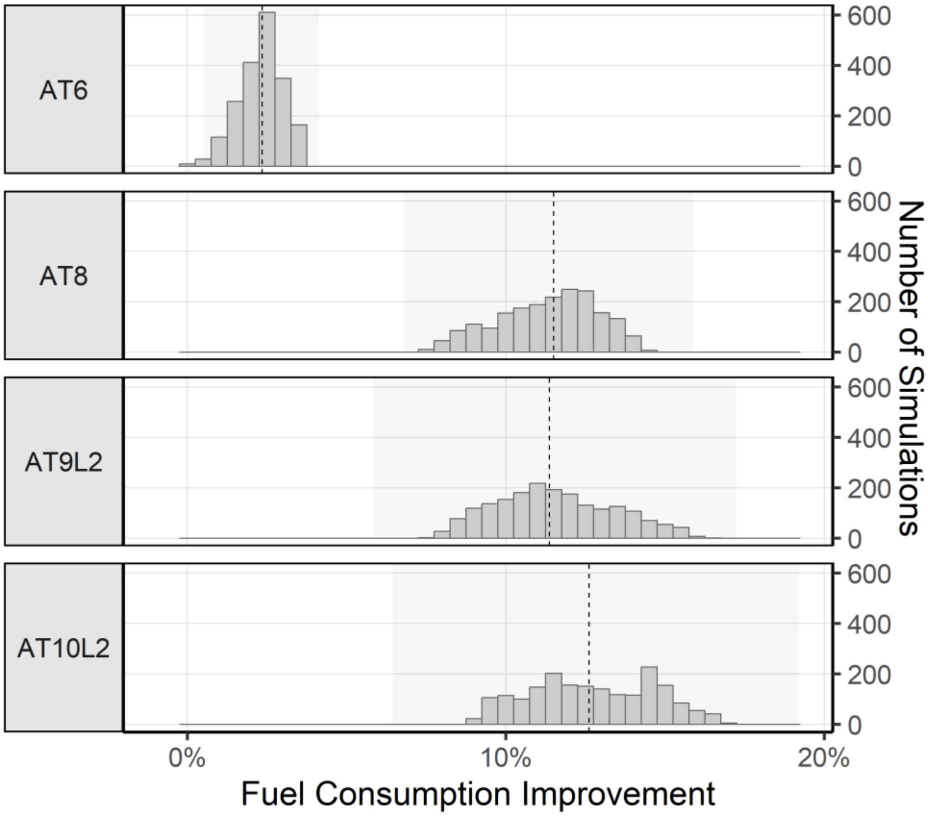


Figure 3-17: HDPUV Transmission Technology Effectiveness Values for All Vehicle Technology Classes



3.2.5. Transmission Costs

The CAFE Model uses both cost and effectiveness in selecting technology updates during the compliance simulation. We use information from sponsored research, CBI, and the NAS to determine direct manufacturing costs (DMCs) for fuel saving technologies.[366] We apply a learning factor and retail price equivalent (RPE) to the DMC to determine the total overall cost of the technology for a given model year (i.e., an absolute cost). The full list of transmission technology costs across all model years, in 2021 dollars, can be found in LD and HDPUV Technologies Input Files. Chapter 4 discusses how we apply the RPE and learning curves to technology DMCs.

This analysis uses absolute costs instead of relative costs, which were used in prior rulemaking analyses. We use absolute costs to ensure the full cost of the transmission is removed when the model applies electrification technologies. This analysis models the cost of adoption of BEV technology by first removing the costs associated with existing powertrain systems, then applying the BEV system costs. An interested reader can still determine relative costs by comparing the absolute costs for the initial technology combination to the new technology combination.

3.2.5.1. Automatic Transmissions

We use AT DMCs from recommended relative costs discussed in the NAS 2015 report and NAS-cited studies. Table 3-61 and Table 3-62 show the LD and HDPUV costs for the AT with learning curve and RPE adjustments applied in the current analysis.

[366] FEV prepared several cost analysis studies for EPA on subjects ranging from advanced 8-speed transmissions to belt alternator starter, or start/stop systems. NHTSA contracted Electricore, EDAG, and Southwest Research for teardown studies evaluating MR and transmissions. The 2015 NAS report on fuel economy technologies for light-duty vehicles also evaluated the agencies' technology costs developed based on these teardown studies.

DMC estimates for all ATs are based on cost estimates from Table 5.7, Table 5.9, and Table 8A.2a of the 2015 NAS report, unless noted otherwise.[367] In the cases of level two (L2) and level three (L3) transmissions, when not already included in the cost estimate, we add the costs for HEG level 2 or level 3 technologies to the base transmission cost.

The AT9 technology DMCs are based on estimates from Table 8A.2a of the 2015 NAS report.[368] The NAS-reported AT9 cost is relative to the AT8 and does not account for the cost of the HEG technology. In our analysis, the AT9 is only equipped with level 2 HEG technology. Therefore, we calculate the costs for the AT9L2 by adding the cost estimate for one additional gear to the AT8L2 cost.[369]

For AT10 technologies, we use DMCs from Table 8A.2a of the 2015 NAS report.[370] The NAS AT10 cost is relative to the AT8 and does not account for the cost of HEG technology. For the current light-duty analysis, the AT10 is only equipped with either level 2 or level 3 HEG technology. The costs for the AT10L2 reflect adding two more gears to the AT8L2. The costs for the AT10L3 reflect adding level 3 HEG technology to AT10L2.

The HDPUV transmission DMCs are based on Table 8A.2a of the 2015 NAS report[371] plus an additional 20%. The 20% increase in DMCs for HDPUVs is an estimate we came to based on comparing the additional weight, torque capacity, and durability required for HDPUVs to similar light-duty vehicle capabilities and their costs from the 2015 NAS report. We believe that the HDPUV transmission costs reasonably represent the HDPUV population as it considers an appropriate range of technology and production volumes.

Table 3-61: Summary of LD Absolute Automatic Transmission Technology Costs for Automatic Transmissions, Including Learning Effects and Retail Price Equivalent in 2021$

Name	Technology Pathway	2020	2022	2026	2030
AT5	Automatic Transmission	$2,248.01	$2,248.01	$2,248.01	$2,248.01
AT6	Automatic Transmission	$2,260.13	$2,260.13	$2,260.13	$2,260.13
AT7L2	Automatic Transmission	$2,472.48	$2,459.64	$2,446.18	$2,439.81
AT8	Automatic Transmission	$2,360.34	$2,360.27	$2,360.15	$2,360.15
AT8L2	Automatic Transmission	$2,625.98	$2,604.50	$2,581.99	$2,571.33
AT8L3	Automatic Transmission	$2,848.45	$2,814.53	$2,778.99	$2,762.15
AT9L2	Automatic Transmission	$2,883.04	$2,848.19	$2,811.65	$2,794.36
AT10L2	Automatic Transmission	$2,883.04	$2,848.19	$2,811.65	$2,794.36
AT10L3	Automatic Transmission	$3,106.14	$3,058.80	$3,009.18	$2,985.70

Table 3-62: Summary of HDPUV Absolute Automatic Transmission Technology Costs for Automatic Transmissions, Including Learning Effects and Retail Price Equivalent in 2021 Dollars

Name	Technology Pathway	2020	2022	2026	2030	2035
AT5	Automatic Transmission	$2,691.61	$2,691.61	$2,691.61	$2,691.61	$2,691.61
AT6	Automatic Transmission	$2,712.16	$2,712.16	$2,712.16	$2,712.16	$2,712.16

367 2015 NAS report, at 189, 298–99.
368 2015 NAS report, at 298-99.
369 2015 NAS report, at 298–99.
370 2015 NAS report, at 298–99.
371 2015 NAS report, at 298-99.

AT8	Automatic Transmission	$2,832.41	$2,832.33	$2,832.18	$2,832.18	$2,832.18
AT9L2	Automatic Transmission	$3,459.66	$3,417.83	$3,373.98	$3,353.24	$3,353.24
AT10L2	Automatic Transmission	$3,459.66	$3,417.83	$3,373.98	$3,353.24	$3,353.24

3.2.5.2. Continuously Variable Transmissions

Table 3-63 shows CVT costs with learning curve and RPE adjustments in 2021 dollars. The DMC for CVT and CVTL2 data comes from the 2015 NAS report Table 8A.2a.

Table 3-63: Summary of LD Absolute Transmission Costs for Continuously Variable Transmissions, Including Learning Effects and Retail Price Equivalent in 2021 Dollars

Name	Technology Pathway	2020	2022	2026	2030
CVT	Continuously Variable Transmission	$2,551.00	$2,545.69	$2,537.07	$2,530.35
CVTL2	Continuously Variable Transmission	$2,751.04	$2,742.07	$2,727.53	$2,716.18

3.2.5.3. Dual Clutch Transmissions

Table 3-64 shows the absolute cost for DCTs with learning curve and RPE adjustments in 2021 dollars. The DMC for the DCTs come from the 2015 NAS report Table 8A.2a.[372]

Table 3-64: Summary of Absolute Transmission Costs for Dual-Clutch Transmissions, Including Learning Effects and Retail Price Equivalent for the Current Analysis in 2021 Dollars

Name	Technology Pathway	2020	2022	2026	2030
DCT6	Dual-Clutch Transmission	$2,316.87	$2,316.84	$2,316.78	$2,316.78
DCT8	Dual-Clutch Transmission	$2,654.56	$2,653.75	$2,653.15	$2,653.02

3.3. Electric Paths

The electric paths include a set of technologies that share common electric powertrain components for certain vehicle functions that were traditionally powered by combustion engines. These technologies range from engine start/stop to the electrification of the entire powertrain (as in the case of an EV).

Unlike other technologies in the analysis, Congress placed specific limitations on how we consider PHEV and BEV fuel economy when determining maximum feasible CAFE standards. In determining maximum feasible fuel economy levels, "the Secretary of Transportation—(1) may not consider the fuel economy of dedicated automobiles; [and] (2) shall consider dual fueled automobiles to be operated only on gasoline or diesel fuel."[373] As discussed in the final rule, NHTSA allows conversions as necessary to reflect anticipated manufacturer compliance with state ZEV programs and voluntary manufacturer vehicle adoption congruent with levels of the ACC II program, but we do impose modeling restrictions to ensure that PHEV and BEV fuel economy is not considered in manufacturer's responses to CAFE standards.

[372] 2015 NAS report, at 298-99.
[373] 49 USC 32902(h)(1), (2).

We implement these restrictions in the CAFE Model by using PHEV fuel economy values assuming the PHEV operates on gasoline-only[374] and by restricting technologies that would convert ICE vehicles in a manufacturer's fleet to a BEV or a FCEV from being applied during "standard-setting" years.[375] While the CAFE Model restricts the application of EV technology in the standard-setting years during the standard-setting model runs, there are several reasons why we must still accurately model EVs in the analysis, which are discussed in detail throughout the preamble. That said, PHEVs, BEVs, and FCEVs only represent a subset of the electrified technologies considered in the analysis. The range of the electrified technologies considered in the CAFE Model is discussed below.

Electrified vehicles can have a partially electrified powertrain, in the case of HEVs or PHEVs, or have a fully electrified powertrain, in the case of BEVs or FCEVs. Among the simpler configurations with the fewest electrification components, micro hybrid technology (SS12V) uses a 12-volt system that simply restarts the vehicle from a stop without regenerative braking functionality. Mild HEVs use a 48-volt belt integrated starter generator (BISG) system that restarts the vehicle from a stop with regenerative braking function. Mild HEVs are also typically capable of a small electric assist to the engine on take-off.

SHEVs have higher system voltages and are capable of start/stop and regenerative braking function, electric motor assist of the engine at higher speeds, and, in many cases, have a limited ability of all-electric propulsion. Common SHEV powertrain architectures, classified by the interconnectivity of common electrified vehicle components, include both a series-parallel power-split architecture (SHEVPS) as well as a parallel architecture (SHEVP2).

PHEVs utilize a combination gasoline-electric powertrain, like that of a SHEV, but also have the ability to plug into the electric grid to recharge the battery, like that of a BEV; this contributes to all-electric mode capability. The analysis includes PHEVs with an AER of 20 and 50 miles to encompass the range of PHEV AER in the market today.

BEVs have an all-electric powertrain and use only batteries for the source of propulsion energy – charged by an external source, like the electric grid. BEVs with ranges of 200 to more than 350 miles are used in the analysis. Like BEVs, FCEVs also have a fully electric powertrain but use a fuel cell system to convert hydrogen fuel into electrical energy.

Table 3-65 below shows an overview of these electrified technologies and their designations. Like other technologies in this analysis, these technologies are not representative of any specific manufacturer's design or architecture; instead, each individual electrification technology encompasses the range of effectiveness and cost for these levels of electrification technologies that exist in industry, for each of the two fleets considered, during the rulemaking timeframe. For example, the BEV2 powertrain efficiency and cost are not intended to represent exactly a Tesla Model 3 or a Nissan Leaf.

[374] We receive two databases of FCIV from the Autonomie modeling, including one with PHEV fuel economy values when operating on gasoline only ("charge sustaining" mode).
[375] CAFE Model Documentation at 36.

Table 3-65: Overview of Electrification Technologies Used in This Analysis

Electric System	Technology Assignment
Micro-Hybrid*	SS12V
Mild-Hybrid**	BISG
Strong Hybrid	SHEVPS and P2 variants
Plug-In Hybrid***	PHEV in 20- and 50-mile range variants
Battery Electric	BEV1, BEV2, BEV3, and BEV4
Fuel Cell Electric	FCEV

*This system does not have engine assist or regeneration braking capabilities.

**Mild Hybrid uses an engine-mounted belt integrated starter generator (BISG).

***PHEVs in this analysis include both power-split (PS) and parallel (P2) hybrid architecture.

See Table 3-66 and Table 3-67 below for further splits within each technology class.

The cost-effectiveness of electrification technologies is based on both battery and non-battery components. The battery strongly influences the cost of electrified vehicles, particularly where the battery is the main source of energy for propulsion of the vehicle. Because developments in battery technology may apply to more than one category of electrified vehicles, they are discussed collectively in Chapter 3.3.5; this subchapter encompasses battery-related topics that directly affect the costing of batteries for all types of electrified vehicles that we consider. See further information on battery direct costs and learning in Chapter 3.3.5.1 and Chapter 3.3.5.3, respectively.

Non-battery electrification components include propulsion components like one or more electric machines — an umbrella term that includes what are commonly known as motor/generators. Electric machines function as motors to provide propulsion and act as generators to enable regenerative braking and the conversion of mechanical energy to electrical energy for storage in the battery.

Non-battery electrification components also include power electronics that process and route electric power between the energy storage and propulsion components. More specifically, power electronics that we include in this analysis are motor controllers, which issue complex commands to control torque and speed of the electric motors precisely; power inverters and rectifiers, which convert and manage direct current (DC) and alternating current (AC) power flows between the battery and the propulsion components; on-board battery chargers, for charging the BEV or PHEV battery from AC line power; and DC/DC converters, to allow for different DC voltages within system circuitry.

In addition, off-board chargers are charging devices that, when plugged into a plug-in electric vehicle (PEV, i.e., a BEV or PHEV), allow charging from the electricity grid. Some off-board chargers, in the case of AC Level 1 charging, travel with the vehicle and are distinct from stationary charging equipment. AC Level 1 chargers, used to charge both BEVs and PHEVs, are powered by a standard household 120V AC power outlet and can deliver approximately 5 miles of range for every 1-hour of charging for BEVs, assuming 1.9kW charging power. AC Level 2 chargers, also used to charge both BEVs and PHEVs, can be installed residentially, at a workplace or publicly, and charges using 208V or 240V AC. Although there is a range of charging power installed today, assuming 6.6kW charging power, AC Level 2 chargers can deliver approximately 25 miles per 1-hour of charging for BEVs. DC fast chargers, found almost exclusively in a public setting and strictly used for BEV charging, charge at rapid rate beyond Level 2 — typically using 480V DC. Depending on the vehicle and the battery's state-of-charge, DC fast chargers are capable of delivering

100-200+ miles range after 30 minutes of charging.[376, 377] As discussed further below, the analysis assumes that BEVs are capable of up to 50kW of DC fast charging for both the light-duty and HDPUVs, and we include the cost of an off-board charger in PEV costs.[378] The process by which the CAFE Model prices non-battery components and adds or subtracts components as necessary to complete the powertrain architecture is discussed in Chapter 3.3.5.

The following subchapters discuss how each electrification technology is defined in the CAFE Model for both the light-duty and HDPUV analysis fleets and the electrification pathways down which a vehicle can travel in response to CAFE standards or reference baseline regulatory scenarios. The subchapters also discuss how we assign electrified vehicle technologies to vehicles in the light-duty and HDPUV analysis fleets, any limitations on electrification technology adoption, and the specific effectiveness and cost assumptions that we use in the Autonomie and CAFE Model analysis.

3.3.1. Electrification Technologies

The CAFE modeling system defines technology pathways for a logical progression of technologies on vehicle groupings. Technologies that share similar characteristics form cohorts that we represent and interpret within the CAFE Model as discrete entities. We lay these entities out into pathways, which the CAFE Model uses to define relations of mutual exclusivity between conflicting sets of technologies.

Table 3-66 and Table 3-67 lists every electrification technology considered in the analysis, including the acronym that we use in the documentation and input files as well as a brief description. For brevity, we refer to technologies by their acronyms in this subchapter.

Table 3-66: CAFE Model Electric Paths Light-Duty Vehicle Technologies

Technology	Description
SS12V	Micro Hybrid-Electric Vehicle, 12-Volt Stop-Start
BISG	Mild Hybrid-Electric Vehicle, 48-Volt Belt Mounted Integrated Starter/Generator
SHEV-P2SGDID	Strong Hybrid-Electric Vehicle, P2 with a Dual Over-Head Cam Engine and Gasoline Direct Injection
SHEV-P2SGDIS	Strong Hybrid-Electric Vehicle, P2 Powertrain with a Single Over-Head Cam Engine and Gasoline Direct Injection
SHEV- P2TRB1	Strong Hybrid-Electric Vehicle, P2 with a TURBO1 Powertrain
SHEV- P2TRB2	Strong Hybrid-Electric Vehicle, P2 with a TURBO2 Powertrain
SHEV- P2TRBE	Strong Hybrid-Electric Vehicle, P2 with a TURBOE Powertrain
SHEV-P2HCR	Strong Hybrid-Electric Vehicle, P2 with a High Compression Ratio Powertrain
SHEV-P2HCRE	Strong Hybrid-Electric Vehicle, P2 with an E-High Compression Ratio Powertrain
SHEV-PS	Strong Hybrid-Electric Vehicle, Power Split (PS) Powertrain
PHEV20PS	Plug-In Hybrid-Electric Vehicle, Power-Split Powertrain and 20-mile All Electric Range
PHEV50PS	Plug-In Hybrid-Electric Vehicle, Power-Split Powertrain and 50-mile All Electric Range
PHEV20T	Plug-In Hybrid-Electric Vehicle, Turbo Engine and 20-mile All Electric Range
PHEV50T	Plug-In Hybrid-Electric Vehicle, Turbo Engine and 50-mile All Electric Range

[376] DOT. 2023. Charger Types and Speeds. Available at: https://www.transportation.gov/rural/ev/toolkit/ev-basics/charging-speeds. (Accessed: Mar. 26, 2024.)
[377] DOE. 2023. Developing Infrastructure to Charge Electric Vehicles. Available at: https://afdc.energy.gov/fuels/electricity_infrastructure.html. (Accessed: Feb. 9, 2024).
[378] Note that this charging rate is slower than most newer BEVs in the market beyond model year 2022, and it is slower than the 150 kW requiremnt for the national netwrok of NEVI chargers.

PHEV20H	Plug-In Hybrid-Electric Vehicle, High Compression Ratio Engine and 20-mile All Electric Range
PHEV50H	Plug-In Hybrid-Electric Vehicle, High Compression Ratio Engine and 50-mile All Electric Range
BEV1	Battery Electric Vehicle, ~200-mile Range $BEV1_{LD} \leq$ 225 miles
BEV2	Battery Electric Vehicle, ~250-mile Range 225 miles < $BEV2_{LD} \leq$ 275 miles
BEV3	Battery Electric Vehicle, ~300-mile Range 275 miles < $BEV3_{LD} \leq$ 350 miles
BEV4	Battery Electric Vehicle, ~400-mile Range 350 miles < $BEV3_{LD}$
FCEV	Fuel Cell Electric Vehicle

Table 3-67: CAFE Model Electric Paths Heavy-Duty Pickup and Van Technologies

Technology	Description
SS12V	Micro Hybrid-Electric Vehicle, 12-Volt Stop-Start
BISG	Mild Hybrid-Electric Vehicle, 48-Volt Belt Mounted Integrated Starter/Generator
SHEV-P2SGDIS	Strong Hybrid-Electric Vehicle, P2 with a Single Over-Head Cam Engine and Gasoline Direct Injection
PHEV50H	Plug-In Hybrid-Electric Vehicle, Single Over-Head Cam Engine and Gasoline Direct Injection and 50-mile All Electric Range
BEV1	Battery Electric Vehicle, ~150-mile Range for Vans and ~200-mile Range for Pickups $BEV1_{HDPUV\_VANS} \leq$ 150 miles and $BEV1_{HDPUV\_TRUCKS} \leq$ 200 miles
BEV2	Battery Electric Vehicle, ~250-mile Range for Vans and ~300-mile Range for Pickups 150 miles < $BEV2_{HDPUV\_VANS} \leq$ 250 miles; 200 miles < $BEV2_{HDPUV\_TRUCKS} \leq$ 300 miles
FCEV	Fuel Cell Electric Vehicle

The technologies that we include on the modeling system's vehicle-level electrification and electric improvements paths for the light-duty analysis – listed above in Table 3-66 – are illustrated in Figure 3-18 below. The HDPUV analysis uses the same levels of electrification improvements as the light-duty analysis, shown above in Table 3-67 and as illustrated in Figure 3-18; however, the HDPUV pathway includes fewer hybrid electric vehicle (HEV) options, and the technology definitions are slightly different (e.g., BEV1 and BEV2 in the light-duty analysis have different AER than BEV1 and BEV2 in the HDPUV analysis), as discussed further below. Additionally, for HDPUVs, we modeled only one type of engine for SHEVs. This was done because our research showed that this assumption is sufficient to represent the SHEV vehicle fleet, as most variability in this type of electrified vehicle exists in the electric machine. More efficiency is gained for less cost by appropriately changing or resizing the electric propulsion components rather than allowing for multiple engines. NHTSA believes that manufacturers will continue to optimize their SHEV powertrains in this way in the future.

As shown in Figure 3-18, the CONV technology is highlighted in orange. This technology identifier is used to denote whether a vehicle comes in with a CONV powertrain (i.e., a vehicle that does not include any level of electrification) and to allow the model to properly map to the Autonomie vehicle simulation database results. If multiple branches converge on a single technology, the subset of technologies disabled from adoption extend only up the point of convergence.

Figure 3-18: Electrification Paths in CAFE Model for LD

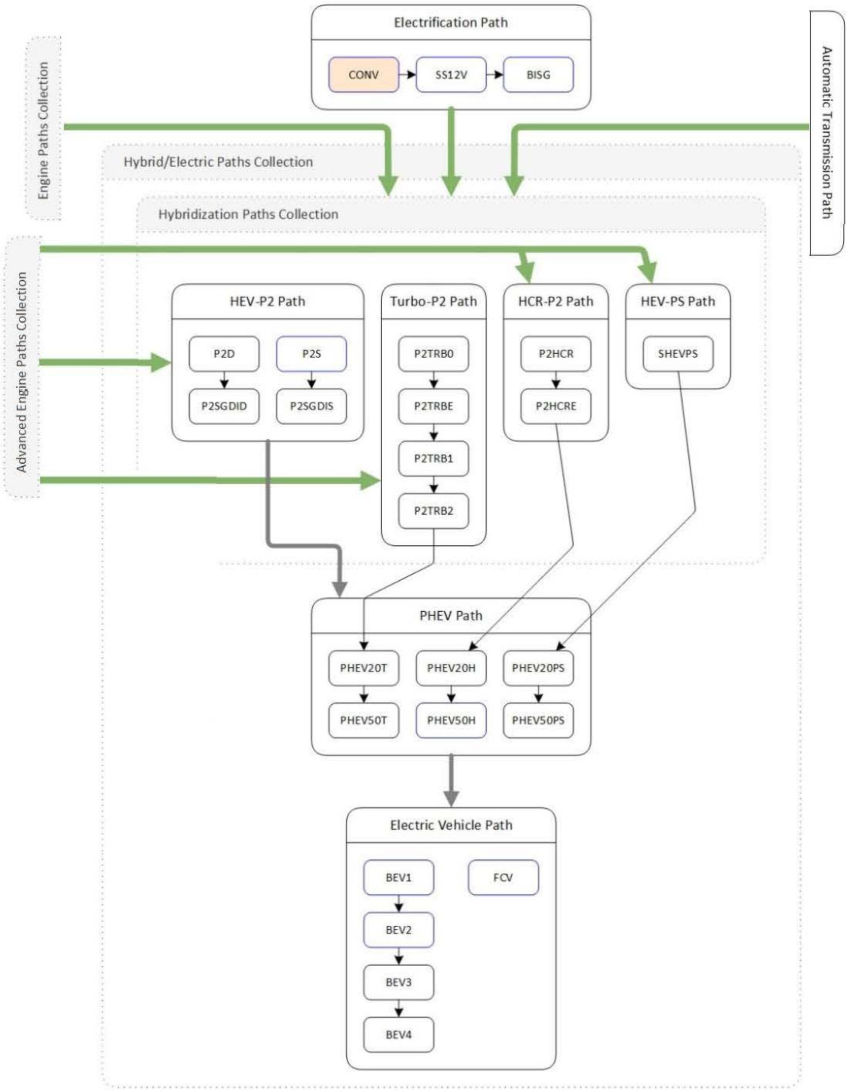
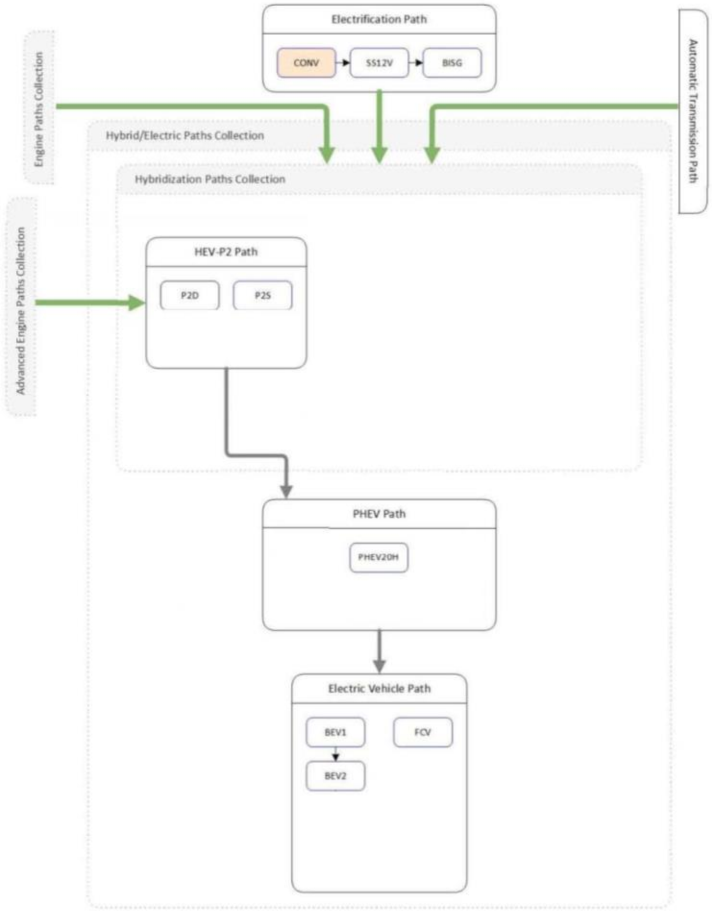


Figure 3-19: Electrification Paths in CAFE Model for HDPUVs



The CAFE Model defines the technology pathway for each type of electrification grouping in a logical progression. Whenever the CAFE Model updates a vehicle model to incorporate additional technology, such as with vehicle electrification, modeling algorithms will update both effectiveness and costs for the vehicle. Additionally, all technologies on the different electrification paths are mutually exclusive and are evaluated in parallel to one another.[379] For example, the model may evaluate plug-in hybrid technology prior to having to apply a mild or strong hybrid technology. We discuss the specific set of algorithms and rules further in the subchapters below and include more detailed discussions in the CAFE Model Documentation. The following subchapters discuss the specifications of each electrification technology used in the analysis.

3.3.1.1. Micro-Hybrids

Micro HEVs utilize SS12V technology, sometimes referred to as start-stop or idle-stop technology, which is considered the most basic hybrid system that facilitates fuel savings. In this system, the integrated starter-generator is coupled to the engine. When the vehicle comes to a stop, the engine completely shuts off. Subsequently, with the help of the 12-volt battery, the engine cranks and starts again in response to throttle application or release of the brake pedal. The 12-volt battery used for the start-stop system is an improved unit compared to a traditional 12-volt battery and is capable of producing more power, increased life cycle, and minimizes voltage drop on restart. This technology is beneficial to reduce fuel consumption and emissions when the vehicle frequently stops, such as in city driving conditions. SS12V can be applied to all vehicle technology classes in both the light-duty and HDPUV analyses.

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[379] See Ch. 2, S4.5 of the CAFE Model Documentation for additional discussions about path mutual exclusivity

3.3.1.2. Mild Hybrids

Mild HEVs, sometimes referred to as P0 hybrids, utilize a belt integrated starter generator (BISG) to provide idle-stop capability as well as regenerative braking function. This system uses a nominal 48-volt battery with increased capacity over conventional automotive batteries. These higher voltages allow the use of a smaller, more powerful and efficient EM/generator, which replaces the standard alternator. In BISG systems, the motor/generator couples to the engine via belt, similar to a standard alternator layout. During engine restart, the BISG turns over the engine. In addition, the BISG can assist vehicle braking and recover braking energy while the vehicle slows down (regenerative braking). In some cases, the BISG system is powerful enough to assist the vehicle when launching from a stop, as with P2/P3 mild hybrids.[380] The CAFE Model assumes that all modeled mild HEVs are 48-volt systems with engine belt-driven motor/generators.

We did not include crank integrated starter generator (CISG) systems, sometimes referred to as a P1 hybrids, in the analysis. A CISG typically has a 48-volt motor/generator that is mounted between the engine and the transmission in a custom housing. CISG systems avoid losses associated with BISG belt slipping; however, they increase the weight of the powertrain and require more significant changes to the powertrain architecture than BISG systems. The size of the motor/generator increases the overall length of the powertrain, often causing packaging and integration issues, and making it difficult for most vehicles to adopt CISG technology. In some cases, the increased length powertrain may not fit in an existing vehicle design. In other cases, the increased size of the powertrain may interfere with other critical powertrain components, such as exhaust and air inlet piping systems that must also be housed in the same space.

The model can apply mild hybrid technology to all vehicle technology classes and all conventional engine technologies in both the light-duty and HDPUV analyses. Chapter 3.3.4 discusses further details of the technology specification and effectiveness.

3.3.1.3. Strong Hybrids

SHEVs are engineered to combine two methods of propulsion within the powertrain to reduce fuel consumption – one method of propulsion being the ICE and the other by means of an electric machine. The electric machine, sometimes referred to as a motor/generator (M/G), also recaptures energy from the vehicle during deceleration or braking that would otherwise be released as heat. Additionally, when the engine is running, the M/G can generate electricity to be stored in the vehicle's on-board battery. This, along with the capability of providing launch and engine assist as well as temporary electric-only operation, allows SHEVs to further reduce fuel consumption by engine downsizing. The effectiveness of SHEVs for improving fuel economy depends on how the above factors are balanced and how the stored energy is applied during powertrain operation. For example, the stored energy may allow for longer periods with the IC engine off or to supplement engine power with the EM to allow the engine to operate at more efficient conditions, potentially in combination with a downsized engine. Conversely, for some performance vehicles, hybrid technologies may be applied primarily for acceleration performance improvement without engine downsizing.

The following strong hybrid systems were included in the analysis: Hybrids with parallel (P2) drivetrain architectures (SHEVP2)[381] and hybrids with series-parallel power-split architectures (SHEVPS).

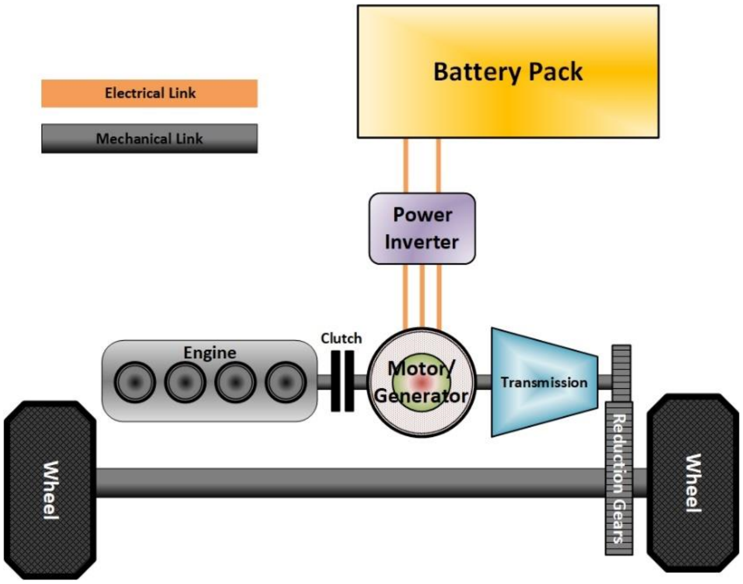
SHEVP2s use a transmission-integrated EM placed between the engine and gearing; a clutch allows for a decoupling of the EM/transmission from the engine. Figure 3-20 below shows the SHEVP2 configuration. Although similar to the configuration of the CISG mild hybrid system discussed previously, generally, a P2 strong hybrid has a more powerful electric motor and a battery with greater capacity in comparison to the CISG system. Disengaging the clutch allows all-electric operation, which is beyond the capability of a CISG system and provides more efficient brake-energy recovery. Re-engaging the clutch allows coupling of the engine and electric machine and, when combined with a transmission, reduces gear-train losses relative to

[380] SEG Automotive. What is 48V/Mild Hybrid drive technology? Available at: https://www.seg-automotive.com/48v/mild-hybrid-technology/. (Accessed: Feb. 9, 2024.)

[381] Depending on the location of electric machine (motor with or without inverter), the parallel hybrid technologies are classified as P0–motor located at the primary side of the engine, P1–motor located at the flywheel side of the engine, P2–motor located between engine and transmission, P3–motor located at the transmission output, and P4–motor located on the axle.

power-split or 2-mode hybrid systems. P2 HEVs typically rely on the ICE to deliver high, sustained power levels. The system enables electric-only mode when power demands are low or moderate.

Figure 3-20: Strong Hybrid Parallel (P2) Powertrain Architecture[382]



An important feature of the SHEVP2 system in our analysis is that it can be applied in conjunction with most engine technologies. Accordingly, once a conventional vehicle is converted to a SHEVP2 powertrain in the compliance simulation, the CAFE Model allows the vehicle to adopt the conventional engine technologies that are the most cost effective, regardless of whether a conventional engine technology is less advanced than the conventional engine technology that the vehicle started with. For example, a vehicle in the model year 2022 analysis fleet that starts with a TURBO2 engine could adopt a TURBO1 engine with the SHEVP2 system if that TURBO1 engine allows the vehicle to meet its fuel economy goal cost effectively. This is based in part on the idea that although manufacturers could adopt SHEVP2 systems into existing powertrain architectures, adopting the SHEVP2 system affords the opportunity for the manufacturer to incorporate a less expensive conventional engine technology alongside it.

In addition, as discussed in Chapter 3.1.1.2.3, the SHEVP2 powertrain improves fuel economy, in part, by allowing the engine to spend more time operating at engine speed and load conditions that have high efficiency. The effectiveness improvement for SHEVP2 is reduced when combined with advanced engine technologies, which also improve fuel economy by broadening the range of engine speed and load conditions where the engine operates at high efficiency. In other words, there is only a minimal additional effectiveness improvement if a SHEVP2 powertrain is combined with an advanced engine, making SHEVP2 less cost effective in those cases. Including a less advanced engine technology with the SHEVP2 powertrain allows a similar efficiency improvement at a lower cost. Chapter 3.3.3 and the CAFE Model Documentation S4 also discuss this logic.

For HDPUVs, towing and work are important part of the vehicle's operation. We selected only SHEVP2 for these types of vehicles in this analysis. SHEVP2 architecture supports high payload and high towing requirements versus other types of hybrid architecture.[383] The mechanical connection between the engine, transmission, and hybrid systems enables continuous power flow to meet high towing weights and loads. Engine downsizing was restricted in this setup to ensure that even when the battery storage system is depleted, the vehicle is still able to complete its operation.

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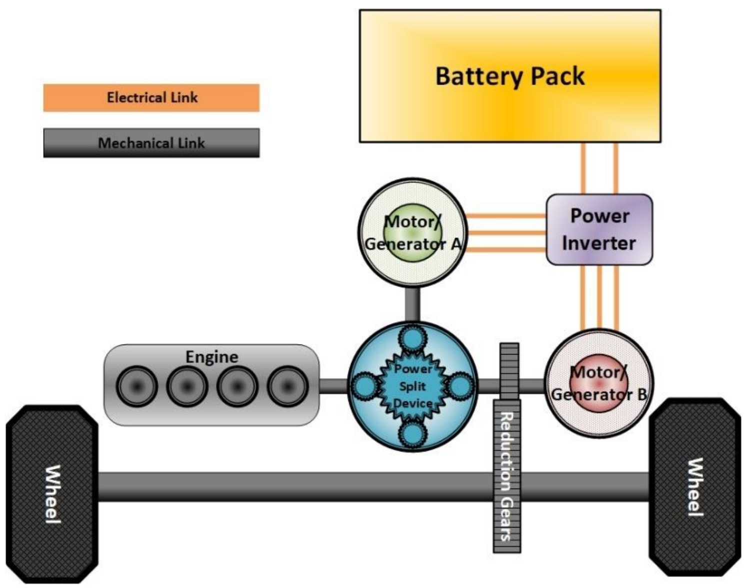
[382] 2015 NAS report, at 133.
[383] Kapadia, J., et al. 2017. Powersplit or Parallel - Selecting the Right Hybrid Architecture. *SAE International Journal of Alternative Power*. Vol. 6(1): at 68-76. Available at: https://doi.org/10.4271/2017-01-1154. (Accessed: Feb. 9, 2024).

Another strong hybrid architecture commonly used in the mainstream automotive industry and covered in this analysis is the series-parallel power-split hybrid architecture (SHEVPS); in this powertrain, the traditional transmission is replaced with a single planetary gear set (the power-split device) and incorporates two motor/generators within its system. As seen in Figure 3-21, Motor/Generator A (M/G-A) generates electricity by motion of the engine either to charge the battery or to supply additional power to the electric drive motor; M/G-A is also used as an electric motor to turn over the engine. A second, more powerful motor/generator, depicted as Motor/Generator B (M/G-B) in the figure and referred to as the “drive motor”, is responsible for propelling the SHEV; M/G-B is connected to the vehicle’s final drive and always turns with the wheels. The planetary gear within the power-split device splits engine power between M/G-A (to charge the battery) and M/G-B (to supply power to the wheels). During vehicle launch or when the battery SOC is high, the engine, which is not as efficient as the electric drive at lower speeds, is turned off and the electric motor propels the vehicle.[384] During normal driving operation, the engine output is used both to propel the vehicle and to generate electricity (via M/G-A) to store in the battery-pack. At higher speeds, both the engine and electric drive motor (by consuming battery energy) work together to propel the vehicle. When braking, the M/G-B can act as a generator to convert the kinetic energy of the vehicle into electricity to charge the battery, granted a permitting battery SOC and temperature.

Figure 3-21 below shows the SHEVPS architecture with the two motor/generator design. The analysis separates the two motor/generators to appropriately size each to maintain performance and to capture the associated costs. Chapter 3.3.4 and Chapter 3.3.5.2 include more discussion of the SHEVPS motor effectiveness and cost.

Figure 3-21: Strong Hybrid Power-Split (PS) Powertrain Architecture[385]



SHEVP2, although enhanced by the electrification components, remains fundamentally similar to a CONV powertrain. In contrast, the SHEVPS is novel and considerably different than a CONV. Although these hybrid architectures are quite different, both types provide start-stop functionality, regenerative braking capability, vehicle launch assist, and engine assist at higher speeds. A SHEVPS has a higher potential for fuel economy improvement than a SHEVP2, although its cost is also higher and engine power density is lower.[386]

To expand on the hybrid powertrain configurations, Table 3-68 below shows the configuration of conventional engines and transmissions used with strong hybrids for this analysis in both the light-duty fleet as well as the HDPUV fleet. The SHEVPS powertrain configuration is paired with a planetary transmission (eCVT) and a

[384] CAFE Analysis Autonomie Documentation, Chapter titled ‘Power-Split HEV’.
[385] 2015 NAS report, at 133.
[386] Kapadia, J., et al. 2017. Powersplit or Parallel - Selecting the Right Hybrid Architecture. *SAE International Journal of Alternative Power*. Vol. 6(1): at 68-76. Available at: https://doi.org/10.4271/2017-01-1154. (Accessed: Feb. 9, 2024).

full-time Atkinson engine.[387] This configuration is designed to maximize efficiency at the cost of reduced towing capability and real-world acceleration performance.[388] In contrast, the SHEVP2 powertrains are paired with an AT8L2 and can be paired with most conventional engines,[389] as discussed above.

Table 3-68: Configuration of Strong Hybrid Architectures with Transmissions and Engines

CAFE Model Technologies	Transmission Options	Engine Options (LD)	Engine Op–ions (HDPUV)
SHEVPS	Planetary - eCVT	Full Time Atkinson engine (Eng26)	N/A
SHEVP2	AT8L2 or eCVT	Most Engines[390]	Naturally Aspirated, SGDI
See further details in Chapter 3.3.4 Electrification Effectiveness.			

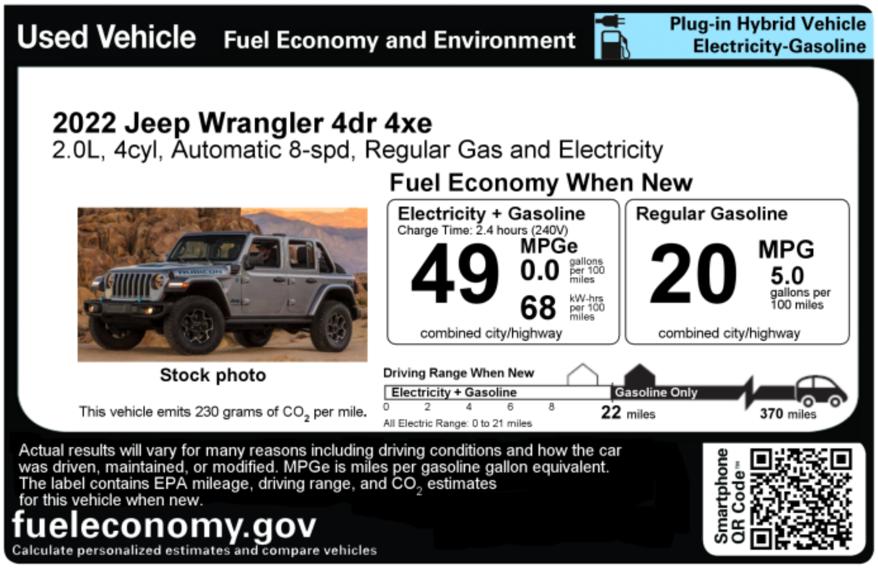
3.3.1.4. Plug-In Hybrids

Unlike the micro, mild, and strong hybrids, all plug-in HEVs (PHEVs) are engineered with the means to charge their battery packs from an outside source of electricity (usually the electric grid). Compared to SHEVs, PHEVs have larger battery packs with more energy storage and a greater electric propulsion capability. PHEVs generally use a control system that allows the battery pack to be substantially depleted under electric-only ("charge depleting") operation or blended mechanical/electric operation; their batteries can be recharged via the engine ("charge-sustaining" operation) at a lower SOC compared to non-PHEVs. Additionally, PHEVs have a significantly greater AER than typical strong HEVs. Depending on how these vehicles are operated, they could, in any particular mode of operation, use electricity exclusively or operate like a strong hybrid.

For CAFE compliance, PHEV gasoline equivalent fuel economy is measured two ways per EPA regulations: first in a "charge depleting mode" with the vehicle operating on electricity with a fully charged battery, and second in a "charge sustaining mode" with the battery depleted and the vehicle propulsion system operating exclusively on gasoline. The overall fuel economy is calculated by weighting the two measured values. Through model year 2015, these two measured values were weighted equally to calculate overall PHEV fuel economy. Optionally beginning in model year 2016 and mandatory beginning in model year 2020, manufacturers use the EPA "utility factor" method for weighting the two measured values for calculating PHEV fuel economy. The "utility factor" weighting is based on the vehicle's AER. The utility factor method follows Society of Automotive Engineers (SAE) recommend practice J1711.[391,392,393,394] As discussed in Chapter 2.3, the Autonomie full vehicle model simulates powertrains accounting for these compliance procedures. Figure 3-22 below shows the fuel economy ratings from the Monroney label[395] that provides both the combined fuel economy ("charge sustaining" and "charge depleting") value as well as the gasoline ("charge sustaining" only) fuel economy.

[387] The Engine we use in CAFE for SHEVPS, PHEV20PS, and PHEV50PS is Eng26. This is first discussed in Chapter 3.1.1.2.3.2 Atkinson Engines – Hybrid Electric Vehicle Engines. We describe Eng26 in various tables in Chapter 3.1 as "HEV-PHEV Atkinson Cycle Engine 1.8L".
[388] Kapadia, J., et al. 2017. Powersplit or Parallel - Selecting the Right Hybrid Architecture. *SAE International Journal of Alternative Power*. Vol. 6(1): at 68-76. Available at: https://doi.org/10.4271/2017-01-1154. (Accessed: Feb. 9, 2024).
[389] We did not model SHEVP2s with VTGE (Eng23c) and VCR (Eng26a).
[390] Eng1, Eng5b, Eng12, Eng13, Eng18, Eng32, Eng33, Eng36, and Eng37. See Chapter 3.1.3 for these engine specifications.
[391] EPA. 2017. EPA Test Procedure for Electric Vehicles and Plug-in Hybrids. DRAFT Summary. Available at: https://fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf. (Accessed: Feb. 9, 2024).
[392] 76 Fed. Reg. 39477, 39504-39505 (Jul. 6, 2011).
[393] 40 CFR 600.116-12(b).
[394] For more detailed information on the development of this SAE utility factor approach, see http://www.SAE.org, specifically SAE J2841. Utility Factor Definitions for Plug-In Hybrid Electric Vehicles Using Travel Survey Data. Sept. 2010 Available at: https://www.sae.org/standards/content/j2841_201009/.
[395] A Monroney Label is a reproduction of the original factory window sticker. U.S. law requires a window sticker, known as a Monroney label, to be displayed on all new cars. These stickers contain mandatory information about the car.

Figure 3-22: Fuel Economy Label for the 2022 Jeep Wrangler 4xe Plug-in Hybrid Showing the Electricity and Gasoline Miles-per-Gallon Equivalent (MPGe)[396]



The methodology that we use to assign fuel economy values to PHEVs in the analysis fleet also accounts for the changes in the regulations and these procedures. These are discussed further in Chapter 2.2 and Chapter 3.3.2.

Four PHEV architectures are included that reflect combinations of two levels of AER (20 and 50 miles) and three engine types (full time Atkinson, HCR, and downsized turbo-charged) that reasonably span the market during the rulemaking timeframe.

PHEV20PS and PHEV50PS can be thought of as SHEVPSs with a larger battery and the ability to drive longer distances with the engine turned off. The PHEV20PS represents a “blended-type” plug-in hybrid, which can operate in all-electric (engine off) mode only at light loads and low speeds and must blend electric motor and engine power together to propel the vehicle at medium or high loads and speeds. The PHEV50PS represents an extended range electric vehicle (EREV), which can travel in all-electric mode even at higher speeds and loads.

PHEV20T/PHEV20H and PHEV50T/PHEV50H are 20-mile and 50-mile AER vehicles based on the SHEVP2 engine architecture. In the CAFE Model, the designation for “H” in PHEVxH represents the HCR engine configuration. The PHEV versions of these architectures include larger batteries and motors to meet performance in charge sustaining mode at higher speeds and loads as well as similar performance and range in all electric mode in city driving at higher speeds and loads. For different PHEV configurations used in this analysis, see Table 3-69 below. Chapter 3.3.4 includes further discussion of PHEV engine sizing, batteries, and motors.

Unlike the light-duty PHEV technologies that include three powertrain options and two range options, our analysis limits the HDPUV PHEV technologies to one powertrain option and one range option. There are no PHEVs in the HDPUV initial analysis fleet, and there are no announcements from major manufacturers that indicate this is a pathway that they will pursue in the short term.[397] NHTSA believes this is in part because PHEVs, which are essentially two separate powertrains combined, can decrease HDPUV capability by increasing the curb weight of the vehicle, thereby reducing cargo capacity. A manufacturer’s ability to use PHEVs in the HDPUV segment is highly dependent on the load requirements and the duty cycle of the

[396] DOE. 2023. Selling Your Vehicle? Advertise Its Fuel Economy! Available at: https://www.fueleconomy.gov/feg/UsedCarLabel.jsp. (Accessed: Feb. 9, 2024).

[397] We recognize that there are some third-party companies that have converted HDPUVs into PHEVs, however, HDPUV incomplete vehicles that are retrofitted with electrification technology in the aftermarket are not regulated under this rule unless the manufacturer optionally chooses to certify them as a complete vehicle. *See* 49 CFR 523.7.

vehicle. However, in the right operation, HDPUV PHEVs can have a cost-effective advantage over their conventional counterparts.[398,399,400] More specifically, there would be a larger fuel economy benefit the more the vehicle could rely on its electric operation, with partial help from the ICE; examples of duty cycles where this would be the case include short delivery applications or construction trucks that drive between work sites in the same city. Accordingly, NHTSA found that PHEVs can be a technology option for adoption in the rulemaking timeframe. The P2 strong hybrid architecture was selected for HDPUV PHEVs because, although there are currently no PHEV HDPUVs in the market to base a technology choice, the P2 strong hybrid architecture would be the most likely selection compared to other architectures for the reasons discussed earlier in Chapter 3.3.1.3. The 50-mile AER was selected for this segment based on discussions with Argonne, who was also involved in DOE projects that provided guidance for this segment.[401,402]

Table 3-69: Configuration of Plug-in Hybrid Architectures with Transmissions and Engines

CAFE Model Technologies	Transmission Options	Engine Options (PC & LT)	Engine Options (HDPUV)
PHEV20H	Planetary - eCVTs	HCR engine	N/A
PHEV20T	AT8L2	Turbo–charged engines	N/A
PHEV20PS	Planetary - eCVTs	Full Time Atkinson Engine	N/A
PHEV50PS	Planetary – eCVTs	Full Time Atkinson Engine	N/A
PHEV50H	AT8L2 (HDPUV) or Planetary - eCVTs (LD)	HCR engine	Naturally Aspirated, SGDI
PHEV50T	AT8L2	Turbo-charged engines	N/A
See further details in Chapter 3.3.4 Electrification Effectiveness.			

3.3.1.5. Battery Electric Vehicles

BEVs are equipped with all-electric drive systems powered by energy-optimized batteries, charged primarily from the electrical grid. BEVs do not have a combustion engine or traditional transmission — instead, BEVs rely on all electric powertrains packaged with an advanced transmission.

In the CAFE Model, we simulate BEVs with ranges that span from below 200 miles to greater than 350 miles; BEV range is measured according to EPA test procedures and guidance.[403] The CAFE Model assumes that

398 National Renewable Energy Laboratory. 2023. Electric and Plug-in Hybrid Electric Vehicle Publications. Transportation & Mobility Research. Available at: https://www.nrel.gov/transportation/fleettest-publications-electric.html. (Accessed: Feb. 9, 2024)
399 For the purpose of the Fuel Efficiency regulation, HDPUVs are assessed on the 2-cycle test procedure similar to the light-duty vehicles. The GVWR does not exceed 14,000 lbs in this segment.
400 Birky, A. et al. 2017. Electrification Beyond Light Duty: Class 2b-3 Commercial Vehicles. Final Report. Dec. 2017. Oak Ridge National Laboratory. pp 1-47. Available at: https://info.ornl.gov/sites/publications/Files/Pub106416.pdf. (Accessed: Feb. 9, 2024).
401 DOE. 21st Century Truck Partnership: Vehicle Technologies Office. Available at: https://www.energy.gov/eere/vehicles/21st-century-truck-partnership. (Accessed: Feb. 9, 2024).
402 Islam, E. et al. 2021. A Detailed Vehicle Modeling & Simulation Study Quantifying Energy Consumption and Cost Reduction of Advanced Vehicle Technologies Through 2050. Department of Energy. Available at: https://www.osti.gov/biblio/1866349. (Accessed: Feb. 9, 2024).
403 EPA. 2017. EPA Test Procedure for Electric Vehicles and Plug-in Hybrids. DRAFT Summary. Available at: https://fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf. (Accessed: Feb. 9, 2024).

BEV transmissions are unique to each vehicle (i.e., the transmissions are not shared by any other vehicle) and that no further transmission-related improvements are available. Table 3-70 below outlines BEV range assignments within the analysis; these values are reflective of the current analysis fleet,[404] with light-duty passenger vehicles capable of longer vehicle ranges from greater powertrain efficiencies and battery advancements. BEV HDPUVs are often used as delivery fleet vehicles[405,406] or utility/service vehicles, and require less range capability compared to light-duty vehicles.[407,408] In partnership with Argonne, we reviewed the available data, as well as feedback from stakeholders and others to converge on the assumptions for BEV ranges in the HDPUV analysis.[409,410,411] NHTSA found that estimates used for this analysis for HDPUVs are reasonable based on the review of both vehicle operations and other studies.

Table 3-70: BEV Range Assignments

BEV Assignment	BEV Range (LD PC/LT)	BEV Range (HDPUV)
BEV1	≤ 225 miles	≤ 150 miles vans ≤ 200 miles trucks
BEV2	> 225 miles; ≤ 275 miles	> 150 miles; ≤ 250 miles for vans > 200 miles; ≤ 300 miles for trucks
BEV3	> 275 miles; ≤ 350 miles	N/A
BEV4	> 350 miles	N/A

An important note about the BEVs used in this analysis is that the CAFE Model does not account for vehicle range when considering additional BEV technology adoption. That is, the CAFE Model does not have an incentive to build BEV3s or BEV4s — the BEV2 is just as efficient as those vehicles and counts the same toward compliance but at a significantly lower cost because of the smaller battery. The analysis looks at adoption of technologies, where applicable, in the percent improvement in the 2-cycle fuel economy space. And so, BEVs tend to be equally efficient when it comes to the percent improvement from conventional technology. Chapter 3.3.4 below shows the effectiveness ranges for BEVS as considered for this analysis. Manufacturers stress that greater range is important for meeting the needs of consumers and to increase consumer demand. More recently, there have been trends towards manufacturers building higher range BEVs in the market — including crossover utility vehicles (CUVs), SUVs, and pickup trucks.[412] To simulate the potential relationship of BEV range to consumer demand, we include several adoption features for BEVs. These are discussed further in Chapter 3.3.3.

404 CAFE Model Documentation.
405 Amazon. 2022. Amazon's Electric Delivery Vehicles from Rivian Roll Out Across the U.S. Last revised: Jul. 21, 2022. Available at: https://www.aboutamazon.com/news/transportation/amazons-electric-delivery-vehicles-from-rivian-roll-out-across-the-u-s. (Accessed: Feb. 9, 2024
406 FedEx. 2022. FedEx Continues Advancing Fleet Electrification Goals with Latest 150 Electric Vehicle Delivery from BrightDrop. Last revised: Jun. 21, 2022. Available at: https://newsroom.fedex.com/newsroom/global/fedex-continues-advancing-fleet-electrification-goals-with-latest-150-electric-vehicle-delivery-from-brightdrop. (Accessed: Feb. 9, 2024).
407 Birky, A. et al. 2017. Electrification Beyond Light Duty: Class 2b-3 Commercial Vehicles. Final Report. Dec. 2017. Oak Ridge National Laboratory. pp 1-47. Available at: https://info.ornl.gov/sites/publications/Files/Pub106416.pdf. (Accessed: Feb. 9, 2024).
408 Karkaria, U. 2023. Mercedes Will Bring Electric Sprinter to U.S. This Year. Automotive News. Last revised: Feb. 7, 2023. Available at: https://www.autonews.com/cars-concepts/mercedes-esprinter-join-competition-us-year. (Accessed: Feb. 9, 2024).
409 Martinez, M. 2022. Detroit 3's Heavy-Duty Trucks Will Keep Status Quo to Get Job Done. Automotive News. Last revised: October 2, 2022. Available at: https://www.autonews.com/sales/heavy-duty-trucks-funding-evs-last-line. (Accessed: Feb. 9, 2024).
410 NREL. 2023. NREL Fleet DNA: Commercial Fleet Vehicle Operating Data. Available at: https://www.nrel.gov/transportation/fleettest-fleet-dna.html. (Accessed: February 9, 2024).
411 DOE. 2022. Incremental Purchase Cost Methodology and Results for Clean Vehicles. Vehicle Technologies Office. Available at: https://www.energy.gov/eere/vehicles/articles/2022-incremental-purchase-cost-methodology-and-results-clean-vehicles. (Accessed: Feb. 9, 2024).
412 Automotive News. More than 50 EVs to join next wave through '24. October 1, 2023. Available at: https://www.autonews.com/future-product/here-are-more-50-evs-coming-market-end-2024. (Accessed: Mar. 28, 2024).

In Chapters 3.3.2 and 3.3.3, we discuss the analysis fleet assignments and adoption features for BEVs, how we rely on Argonne's expertise and other sources to evaluate effectiveness and performance, and how we determine costs for both the battery and non-battery electrification components.

3.3.1.6. Fuel Cell Electric Vehicles

Similar to BEVs, FCEVs are equipped with an all-electric drivetrain, but unlike BEVs, FCEVs do not solely rely on batteries to store energy; rather, electricity to run the FCEV's electric motor is mainly generated by an on-board fuel cell system.[413] FCEV architectures are similar to series hybrids[414] but with the engine and generator replaced by a fuel cell. Commercially available FCEVs consume hydrogen to generate electricity for the fuel cell system with most automakers using high pressure gaseous hydrogen storage tanks. FCEVs are currently produced in limited numbers and are only available in limited geographic areas where hydrogen refueling stations are accessible. For reference, in model year 2022, only four different FCEV models were offered for sale, and since 2014 only 17,846 FCEVs have been sold.[415,416]

For this analysis, the CAFE Model simulates a FCEV with a range of 300 miles for both light-duty and heavy-duty pickup trucks and 250 miles for heavy-duty vans. Any type of powertrain could adopt a FCEV powertrain; however, to account for limited market penetration and unlikely increased adoption in the rulemaking timeframe,[417] technology phase-in caps were used to control how many FCEVs a manufacturer could build. The details of this concept are further discussed in Chapter 3.3.3.

3.3.2. Assigning Electrification Technologies in the Analysis Fleet

Electrification technologies present in the analysis fleets were identified as the starting point for the regulatory analysis. These assignments are based on manufacturer-submitted CAFE compliance information, publicly available technical specifications, marketing brochures, articles from reputable media outlets, and data from Wards Intelligence.[418]

Table 3-66 and Table 3-67, in Chapter 3.3.1, list every electrification technology considered in the analysis, including the acronym that we use in the documentation and input files as well as a brief description of the technology.

Table 3-71 and Table 3-72 below expand on these electrification technologies and give the initial penetration rates of eligible electrification technologies in the light-duty and HDPUV analysis fleets respectively. Over half the light-duty fleet has some level of electrification, with the vast majority of these being micro hybrids; BEV3 is the most common BEV technology. The HDPUV fleet only has a conventional non-electrified powertrain, currently.

Table 3-71: Penetration Rate of Electrification Technologies in the MY 2022 Light-Duty Fleet

Electrification Technology	Sales Volume with this technology	Penetration Rate in 2022 Analysis Fleet
None	4,245,656	29.41%
SS12V	7,569,293	52.43%
BISG	583,785	4.04%
SHEVP2	245,778	1.70%
SHEVPS	745,535	5.16%

[413] FCEVs use a propulsion system similar to that of electric vehicles, where energy stored as hydrogen is converted to electricity by the fuel cell.
[414] Series hybrid architecture has a power-flow structure with the engine, electric motor, and transmission in series. In this architecture, the engine does not propel the vehicle; instead, it drives a generator to charge the battery.
[415] Argonne National Lab. 2023. Light Duty Electric Drive Vehicles Monthly Sales Update. Energy Systems Division. Available at: https://www.anl.gov/esia/light-duty-electric-drive-vehicles-monthly-sales-updates. (Accessed: Feb. 9, 2024
[416] Market Data Input File: Hyundai Nexo (Limited and Blue) and Toyota Mirai (XLE and Limited).
[417] Rho Motion subscription. EV & Battery Quarterly Outlook: Quarter 3, 2023. Available at: https://rhomotion.com/. (Accessed: Jan. 8, 2024)
[418] Wards Intelligence. 2022. U.S. Car and Light Truck Specifications and Prices, '22 Model Year. Last revised: Apr. 4, 2022. Available at: https://wardsintelligence.informa.com/WI966023/US-Car-and-Light-Truck-Specifications-and-Prices-22-Model-Year. (Accessed: Feb. 9, 2024).

PHEV20PS	31,966	0.22%
PHEV20H	50,643	0.35%
PHEV20T	132,181	0.92%
PHEV50PS	0	0.000%
PHEV50H	27,776	0.19%
PHEV50T	200	0.001%
BEV1	45,754	0.32%
BEV2	233,631	1.62%
BEV3	389,752	2.70%
BEV4	129,860	0.90%
FCEV	4,419	0.03%
TOTAL	14,436,229	100%

Table 3-72: Penetration Rate of Electrification Technologies in the Analysis HDPUV Fleet

Electrification Technology	Sales Volume with this technology	Penetration Rate in Analysis Fleet
None	821,579	100%
SS12V	0	0.00%
BISG	0	0.00%
SHEVP2	0	0.00%
PHEV50H	0	0.00%
BEV1	0	0.00%
BEV2	0	0.00%
FCEV	0	0.00%
TOTAL	821,579	100%

3.3.2.1. Micro and Mild Hybrids

Micro and mild hybrids refer to the presence of SS12V and BISG, respectively. The data sources discussed above were used to identify the presence of these technologies on vehicles in the fleet. Micro and mild hybrid technology were only assigned if we could confirm its presence with manufacturer brochures or technical specifications.

3.3.2.2. Strong Hybrids

Strong hybrid technologies include SHEVPS and SHEVP2. For a discussion of differences in architecture between these technologies, see Chapter 3.3.1.3. Note that P2HCRE is not assigned in the fleet and is only available to be applied by the model. When possible, manufacturer specifications are used to identify the strong hybrid architecture type. In the absence of more sophisticated information, we determine hybrid architecture by number of electric motors. Hybrids with one electric motor are designated “P2”, and those with two electric motors “PS”.

3.3.2.3. Plug-In Hybrids

Plug-in hybrid technologies that we assign in the analysis fleet include PHEV20PS/20H/20T and PHEV50PS/50H/50T. We assign vehicles with an electric-only range of 40 miles or less as PHEV20; we assign those with a range above 40 miles as PHEV50. For the purpose of modeling cost and benefits, these two ranges are appropriate to cover most of the PHEVs in the market now. These ranges are also a combination of market review for PHEVs and reports showing that they are typical for short commutes.[419,420] We assign vehicles as PHEV20T/50T if the engine is turbocharged (i.e., if it would qualify for one of technologies on the turbo engine technology pathway).[421] We assign vehicles that qualify for full time Atkinson cycle engines, such as the Toyota Prius Prime, as PHEV20S/50S.

We calculate individual gasoline and electric fuel economy values as part of characterizing PHEVs in the analysis fleet[422]– using the "charge sustaining" (gasoline) fuel economy for light-duty vehicles in the "standard setting" runs, and using both "charge sustaining" (gasoline) and "charge depleting" (electric) fuel economy for the "real-world" or EIS CAFE Model runs, and for all heavy-duty pickups and vans.[423] This is necessary because the certification fuel economies for PHEVs reported in compliance data are a single value that combine both types of fuel economies. To calculate PHEV gas fuel economy, we scale values derived from fueleconomy.gov by a factor of 1.3;[424] the scaled gas fuel economy becomes the final value that we use in the Market Data Input File for light-duty vehicles.

To compute electric ("charge depleting") fuel economy, we calculate utility factors, which define the proportion of miles traveled by PHEVs using electricity according to mathematical curves defined by SAE.[425] These curves use each vehicle's all electric range (AER) as the input; range values are derived from the same source as the analysis fleets' gas fuel economy values and are also scaled by a factor of 1.3. Analyst-defined utility factors or a default value of 0.5[426] are also an option for each PHEV. Of the three possible utility factors — the calculated value with the factor of 1.3, the analyst-defined value, or the default 0.5 value — we applied the greatest value.

The SAE standard is then used for calculating the utility factor-weighted electric fuel economy[427] while defining a functional relationship to calculate it from known values, which is given in Equation 3-1. Note that the equation is divided by the current petroleum equivalency factor (PEF), because this factor is later accounted for in the model for model year 2022 to 2026.[428] Starting in model year 2027, the equation is divided by a new value based on the newly DOE-finalized petroleum equivalency factor.

Equation 3-1: Electric Fuel Economy

$$\textit{Electric Fuel Economy} = \frac{(\textit{Certification FE}) \times (\textit{Scaled Gas FE}) \times (\textit{Utility Factor})}{(\textit{Scaled Gas FE} - \textit{Certification FE}) \times (1 - \textit{Utility Factor})} \times \frac{1}{\textit{PEF}}$$

This approach has some limitations. In some cases, the electric fuel economy values or utility factors are not reported by manufacturers. This is due to the certification fuel economy values that manufacturers report in compliance data, which are often not broken down to the specific level that is needed for compliance analysis. Determining the electric range of PHEVs is complicated if the vehicle can operate in blended modes.[429] For

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419 Perks, R., Raborn, C. 2013. Driving Commuter Choice in America: Expanding Transportation Choices Can Reduce Congestion, Save Money and Cut Pollution. NRDC IP.13-06A. Available at: https://www.nrdc.org/sites/default/files/driving-commuter-choice-IP.pdf. (Accessed: Feb. 9, 2024).
420 DOE. 2018. FOTW #1047, September 17, 2018: Daily Vehicle Miles Traveled Varies with the Number of Household Vehicles. Office of Energy Efficiency and Renewable Energy. Available at: https://www.energy.gov/eere/vehicles/articles/fotw-1047-september-17-2018-daily-vehicle-miles-traveled-varies-number. (Accessed: Feb. 9, 2024).
421 See Chapter 3.1.1.2.2 for more information on turbocharged engines in the analysis.
422 Calculating PHEV fuel economy is determined for the purpose of fuel economy compliance for the effects on the EIS analysis.
423 For CAFE standards setting runs, only the "charge sustaining" (gasoline only) operation is used for effectiveness calculation for the light-duty vehicles. However, the full combined operation ("charge depleting" and "charge sustaining") is used for EIS setting runs for effectiveness calculation for the light-duty vehicles. For HDPUV, the combined operation is used for effectiveness calculation for both the heavy-duty Fuel Efficiency standard setting runs and EIS runs.
424 The 1.3 scalar value accounts for the adjustment procedure used by EPA when deriving the Monroney fuel economy label ("window sticker") values, which are calculated by multiplying measured fuel economies by a factor of 0.7. More information can be found at https://www.fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf. (Accessed: Feb. 9, 2024).
425 SAE International. 2010. Utility Factor Definitions for Plug-In Hybrid Electric Vehicles Using Travel Survey Data. Available at: www.sae.org/standards/content/j2841_201009. (Accessed: Feb. 9, 2024).
426 A utility factor of 0.5 indicates that exactly half of a PHEV's miles traveled are on gas fuel, while the other half are on electric power.
427 SAE International. 2010. Recommended Practice for Measuring the Exhaust Emissions and Fuel Economy of Hybrid-Electric Vehicles, Including Plug-in Hybrid Vehicles. Available at: www.sae.org/standards/content/j1711_201006. (Accessed: Feb. 9, 2024).
428 Equation 26 the petroleum equivalency factor of electricity discussed in the CAFE Model Documentation S5.1.1. The scalar term, used in the CAFE Model Documentation equation, is 82,049 Wh/gal through model year 2026 and updated to new values starting in model year 2027.
429 2023 EPA Trends Report at E-1.

PHEVs like the Ford Escape, which cannot operate in blended mode, the electric range represents the estimated range operating in electric only mode. However, for PHEVs that operate in a blended mode, the electric range represents the estimated range of the vehicle operating in either electric only or blended mode, due to the design of the vehicle. For example, the BMW X5 uses electricity stored in its battery and a small amount of gasoline to achieve an alternative fuel range. Some PHEVs did not use any gasoline to achieve their electric range value on EPA test cycles; however, certain driving conditions (e.g., more aggressive accelerations, higher speeds) would likely cause these vehicles to operate in a blended mode instead of an all-electric mode.

For more information on the calculation methodology for PHEVs, please see CAFE Model Documentation S5.1.1

3.3.2.4. Fuel Cell and Battery Electric Vehicles

FCEV and BEV technologies include BEV1/2/3/4 and FCEV. Vehicles with all-electric powertrains that used hydrogen fuel are assigned FCEV. The BEV technologies are assigned to vehicles based on range according to the thresholds listed previously in Table 3-70. These range thresholds best account for vehicles' existing range capabilities while allowing room for the model to potentially apply more advanced electrification technologies.

3.3.3. Electrification Adoption Features

We apply several adoption features to the electrification technologies. The hybrid/electric technology path logic dictates how vehicles could adopt different levels of electrification technology. Figure 3-18 and Figure 3-19 in the previous subchapter showed the electrification technology pathways – applicable for both light-duty vehicles and heavy-duty pickups and vans; these are discussed in detail in each technologies' subchapter below. Broadly speaking, more advanced levels of hybridization or electrification supersede all prior levels, while certain technologies within each level are mutually exclusive. We model (from least to most electrified) micro hybrids, mild hybrids, strong hybrids, plug-in hybrids, and battery-electric and fuel cell electric vehicles.[430]

As discussed further below, SKIP logic — constraints on the adoption of certain technologies — apply to PHEVs and SHEVs. Some technologies on these pathways are "skipped" if a vehicle is high performance, requires high towing capabilities as a pickup truck, or belongs to certain manufacturers who have demonstrated that their future product plans will likely not include the technology. We expand on the specific criteria for SKIP logic for each applicable electrification technology later in this subchapter.

This subchapter also discusses the supersession of engines and transmissions on vehicles that adopt SHEV or PHEV powertrains. To manage the complexity of the analysis, we model these types of hybrid powertrains with several specific engines and transmissions, rather than in multiple configurations. The SHEV and PHEV cost and effectiveness values account for these specific engines and transmissions.

Finally, phase-in caps limit the adoption rates of BEVs and FCEVs across the rulemaking timeframe. These phase-in caps account for current market share, scalability, and reasonable consumer adoption rates of each technology. Chapter 3.3.3.4 discusses phase-in caps and the reasoning behind them in detail.

The following subchapters discuss the adoption features that the model applies to each type of electrification technology.

3.3.3.1. Micro and Mild Hybrids

For this analysis, micro and mild hybridization refer to the presence of SS12V and BISG technology on a vehicle, respectively. The only adoption feature for these technologies is path logic, as illustrated in Figure 3-18 and Figure 3-19 under Chapter 3.3.1. The pathway consists of a linear progression starting with a CONV – absent of electrification – which is superseded by SS12V, which, in turn, is superseded by BISG.

[430] See CAFE Model Documentation for additional description of how path logic is applied.

Vehicles can only adopt micro and mild hybrid technology if the vehicle did not already have a more advanced level of electrification.

3.3.3.2. Strong Hybrids

The SHEV technologies in the light-duty fleet include series-parallel power-split powertrains (SHEVPS) and parallel powertrains (SHEVP2SGDID, SHEVP2SGDIS, P2TRB1, P2TRB2, P2TRBE, P2HCR, and P2HCRE). The HDPUV fleet is restricted to only including P2 strong hybrid technology SHEV-P2SGDIS – the model restricts adoption of HCR engine technology or power-split hybrid technology (SHEVPS). See Table 3-71 and Table 3-72 for further SHEV technology details. Unlike the light-duty fleet, we do not allow downsizing for HDPUVs where towing and/or hauling are an essential part of their utility requirements. In these cases, if the engine is downsized, the battery can be quickly drained during a long hill climb with a heavy load, leaving only a downsized engine to carry the entire load. Because towing capability is currently an important truck attribute, manufacturers are hesitant to offer a truck with downsized engine which can lead to a significantly diminished towing performance when the battery state of charge level is low, and therefore engines are traditionally not downsized for these vehicles.

The adoption features that we apply to strong hybrid technologies include path logic, powertrain substitution, and vehicle class restrictions. Per the defined (applicable) technology pathways, SHEVPS, SHEVP2x, SHEVP2TRBx, and the P2HCRx technologies are considered mutually exclusive. In other words, when the model applies one of these technologies, the others are immediately disabled from future application. However, all vehicles on the strong hybrid pathways can still advance to one or more of the plug-in technologies.

When the model applies any strong hybrid technology to a vehicle, the transmission technology on the vehicle is superseded; regardless of the transmission originally present, P2 hybrids adopt an AT8L2, and series-parallel power-split (PS) hybrids adopt a CVT via power-split device (eCVT). When the model applies the SHEVP2 technology, the model can consider various engine options to pair with the SHEVP2 architecture according to existing engine path constraints — taking into account relative cost effectiveness. For SHEVPS technology, the existing engine is replaced with a full time Atkinson cycle engine.[431]

SKIP logic is also used to constrain adoption for SHEVPS and PHEV20/50PS. These technologies are "skipped" for vehicles with engines[432] that meet one of the following conditions:

- The engine belongs to an excluded manufacturer;[433]
- The engine belongs to a pickup truck (i.e., the engine is on a vehicle assigned the "pickup" body style);
- The engine's peak horsepower is more than 405 hp; or if
- The engine is on a non-pickup vehicle but is shared with a pickup.

The reasons for these conditions are similar to those for the SKIP logic that we apply to HCR engine technologies, discussed in more detail in Chapter 3.1.1.2.3. In the real world, performance vehicles with certain powertrain configurations cannot adopt the technologies listed above and maintain vehicle performance without redesigning the entire powertrain. SKIP logic is put in place to prevent the model from pursuing compliance pathways that are ultimately unrealistic.

No SKIP logic applies to SHEVP2. We believe that this type of electrified powertrain is sufficient to meet all of the performance requirements for all types of vehicles. Manufacturers have proven this with vehicles such as the Ford F-150 Hybrid and Toyota Tundra Hybrid.[434,435]

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[431] Designated Eng26 in the list of engine map models used in the analysis. See Chapter 3.1.1.2.3 for more information.
[432] This refers to the engine assigned to the vehicle in the 2022 baseline fleet.
[433] Excluded manufacturers included BMW, Daimler, and JLR.
[434] Buchholz, K. 2021. 2022 Toyota Tundra: V8 Out, Twin-Turbo Hybrid Takes Over. SAE International. Last revised: Aug. 22, 2021. Available at: https://www.sae.org/news/2021/09/2022-toyota-tundra-gains-twin-turbo-hybrid-power. (Accessed: Feb. 9, 2024).
[435] Visnic, B. 2020. Hybridization the Highlight of Ford's All-new 2021 F-150. SAE International. Last revised: June 30, 2020. Available at: https://www.sae.org/news/2020/06/2021-ford-f-150-reveal. (Accessed: Feb. 9, 2024).

3.3.3.3. Plug-In Hybrids

Plug-in hybrid-electric vehicle (PHEV) technologies include PHEV20PS/20H/20T and PHEV50PS/50H/50T. They supersede the micro, mild, and strong hybrids and can only be replaced by fully electric technologies. Plug-in hybrid technology paths are also mutually exclusive, with the PHEV20 technologies able to progress to the PHEV50 technologies.

light-duty PHEV technologies include series-parallel power-split powertrains (PHEVx0PS) and parallel powertrains (PHEVx0T and PHEVx0H). The HDPUV fleet is restricted to only adopting PHEV50H technology as discussed earlier in Chapters 3.3.1.3 and 3.3.1.4 – the model restricts adoption of power-split hybrid technology (PHEVx0PS). See Table 3-71 and Table 3-72 for further PHEV technology details. There are no other constraints for PHEVs for the light-duty analysis, and the model will apply PHEV powertrains if it deems them cost effective. For the HDPUV analysis, PHEV technology is not available in the model until model year 2025 for heavy-duty vans and model year 2027 for heavy-duty pickups, for reasons discussed in Chapter 3.3.1.4. The technology is fully available for adoption by HDPUVs in the rulemaking timeframe (i.e., model years 2030 and beyond).

The engine and transmission on a vehicle are superseded when PHEV technologies are applied. For example, the model applies an AT8L2 transmission with all PHEV20T/50T plug-in technologies, and the model applies an eCVT transmission for all PHEV20PS/50PS and PHEV20H/50H plug-in technologies. A vehicle adopting PHEV20PS/50PS receives a hybrid full Atkinson cycle engine,[436] and a vehicle adopting PHEV20H/PHEV50H receives an HCR engine.

3.3.3.4. Fuel Cell and Battery Electric Vehicles

Adoption of BEVs and FCEVs is limited by both path logic and phase-in caps. They are applied as end-of-path technologies that supersede previous levels of electrification.

The main adoption features applicable to BEVs and FCEVs are phase-in caps, which are defined in the CAFE Model Input File as percentages that represent the maximum rate of increase in penetration rate for a given technology. Phase-in caps are accompanied by a phase-in start year, which determines the first year the phase-in cap applies. Together, the phase-in cap and start year determine the maximum penetration rate for a given technology in a given year; the maximum penetration rate equals the phase-in cap times the number of years elapsed since the phase-in start year. Note that phase-in caps *do not* inherently dictate how much a technology is applied by the model. Rather, they represent how much of the fleet *could* have a given technology by a given year. Because BEV1 costs less and has slightly higher effectiveness values[437] than other advanced electrification technologies, the model will have vehicles adopt it first, until it is restricted by the phase-in cap.

Table 3-73 shows the phase-in caps, phase-in year, and maximum penetration rate through 2050 for BEV and FCEV technologies for both the light-duty and HDPUV fleet. For comparison, we also list the actual penetration rate of each technology in the 2022 analysis fleet in the fourth column from the left.

[436] Designated Eng26 in the list of engine map models used in the analysis. See Chapter 3.1.2 and Chapter 3.1.3 for more information.
[437] This is because BEV1 uses fewer batteries and weighs less than BEVs with greater ranges.

Table 3-73: Phase-In Caps for Fuel Cell and Battery Electric Vehicle Technologies

Fleet	Technology Name	Phase-In Cap	Phase-In Start Year	Actual Penetration Rate in 2022 (Analysis Fleet)	Maximum Penetration Rate in 2022	Maximum Penetration Rate in 2025	Maximum Penetration Rate in 2030	Maximum Penetration Rate in 2035	Maximum Penetration Rate in 2040	Maximum Penetration Rate in 2045	Maximum Penetration Rate in 2050
LD	BEV1	0.09%	1998	0.32%	2.16%	2.43%	2.88%	3.33%	3.78%	4.23%	4.68%
	BEV2	0.50%	2009	1.62%	6.50%	8.00%	10.50 %	13.00 %	15.50 %	18.00 %	20.50 %
	BEV3	1.80%	2016	2.70%	10.80 %	16.20 %	25.20 %	34.20 %	43.20 %	52.20 %	61.20 %
	BEV4	2.75%	2021	0.90%	2.75%	11.00 %	24.75 %	38.50 %	52.25 %	66.00 %	79.75 %
	FCEV	0.018 %	2016	0.03%	0.108 %	0.162 %	0.252 %	0.342 %	0.432 %	0.522 %	0.612 %
HDPUV	BEV1	6.00%	2021	-	6.00%	24.00 %	54.00 %	84.00 %	100%	100%	100%
	BEV2	10.00 %	2021	-	10.00 %	40.00 %	90.00 %	100%	100%	100%	100%
	FCEV	0.018 %	2016	-	0.108 %	0.162 %	0.252 %	0.342 %	0.432 %	0.522 %	0.612 %

The light-duty BEV1 phase-in cap is informed by manufacturers' tendency to move away from low-range passenger vehicles offerings in part because of potential consumer concern with range anxiety.[438,439,440] In some cases, the advertised range on most EVs may not reflect the actual real-world range in cold and hot ambient temperatures and real-world driving conditions, affecting the utility of these lower range vehicles.[441,442] Many manufacturers have told us that the portion of consumers willing to accept a vehicle with the lowest modeled range is small, with manufacturers targeting range values above BEV1 range for this reason.[443]

[438] Lutz, H. 2023. Automotive News. U.S. consumer interest in EVs gains, but still trails other nations. Available at: https://www.autonews.com/mobility-report/ey-study-consumer-interest-evs-gains-still-trails-other-nations. (Accessed: Mar. 28, 2024).
[439] 2023 EPA Trends Report at 64.
[440] IEA. 2022. Trends in Electric light-duty vehicles. Available at: https://www.iea.org/reports/global-ev-outlook-2022/trends-in-electric-light-duty-vehicles. (Accessed: Feb. 9, 2024).
[441] AAA. 2019. AAA Electric Vehicle Range Testing. Last Revised: Feb. 2019. Available at: https://www.aaa.com/AAA/common/AAR/files/AAA-Electric-Vehicle-Range-Testing-Report.pdf. (Accessed: Feb. 9, 2024).
[442] Pratt, D. 2021. How Much Do Cold Temperatures Affect an Electric Vehicle's Driving Range? Consumer Reports. Last revised: Dec. 19, 2021. Available at: https://www.consumerreports.org/hybrids-evs/how-much-do-cold-temperatures-affect-an-evs-driving-range-a5751769461. (Accessed: Feb. 9, 2024).
[443] Randall, T. 2023. Bloomberg News. California Shows an Electric-Car Uprising Headed for the US.. Available at: https://www.bnnbloomberg.ca/california-shows-an-electric-car-uprising-headed-for-the-us-1.1968891. (Accessed: Mar. 28, 2024)

Furthermore, the average BEV range has steadily increased over the past decade,[444] due to battery technological breakthroughs increasing energy density[445,446] as well as batteries becoming more cost effective.[447] EPA observed in its 2023 Automotive Trends Report that "the average range of new EVs has climbed substantially. In model year 2022, the average new EV range is 305 miles, or more than four times the range of an average EV in 2011."[448] Based on the cited examples and basis described in this subchapter, the maximum growth rate for light-duty BEV1s in the model is set accordingly low to less than 0.1 percent per year. While this rate is significantly lower than that of the other BEV technologies, the BEV1 phase-in cap allows the penetration rate of low-range BEVs to grow by a multiple of what is currently observed in the market.

For higher BEV ranges (such as that for BEV2 for both light-duty and HDPUVs), phase-in caps are intended to conservatively reflect potential challenges in the scalability of BEV manufacturing, and implementing BEV technology on many vehicle configurations, including larger vehicles. In the short term, the penetration of BEVs is largely limited by affordability, determined battery material acquisition, processing, and manufacturing.[449,450,451] Incorporating battery packs with the capacity to provide greater electric range also poses its own engineering challenges. Heavy batteries and large packs may be difficult to integrate for many vehicle configurations and require vehicle structure modifications. Pickup trucks and large SUVs in particular require higher levels of energy as the number of passengers and/or payload increases, for towing and other high-torque applications. In the light-duty analysis, we use the light-duty BEV3 and BEV4 phase-in caps to reflect these transitional challenges and use similar phase-in caps for the HDPUV analysis.

The phase-in cap for FCEVs is assigned based on existing market share as well as historical trends in FCEV production for light-duty and HDPUV. FCEV production share in the past five years has been extremely low[452] and lack of fueling infrastructure remains a limiting factor[453] – we set the phase-in cap accordingly. As with BEV1, however, the phase-in cap still allows for the market share of FCEVs to grow several times over.

3.3.4. Electrification Effectiveness

For this analysis, we consider a range of electrification technologies which, when modeled, result in varying levels of effectiveness at reducing fuel consumption. As discussed above, the modeled electrification technologies include micro hybrids, mild hybrids, two different strong hybrids, three different plug-in hybrids with two separate all electric ranges, battery electric vehicles of various ranges, and fuel cell electric vehicles. Each electrification technology consists of many complex subsystems with unique component characteristics and operational modes. As discussed further below, the systems that contribute to the effectiveness of an electrified powertrain in the analysis include the vehicle's battery, electric motor/generator(s), power electronics, and accessory loads. We discuss the procedures for modeling each of these subsystems in Chapter 3.2 and in the CAFE Analysis Autonomie Documentation.

Argonne uses data from their Advanced Mobility Technology Laboratory (AMTL) to develop Autonomie's electrified powertrain models. The modeled powertrains are not intended to represent any specific manufacturer's architecture but act as surrogates by predicting representative levels of effectiveness for each electrification technology.

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444 2023 EPA Automotive Trends Report, at 64, Figure 4.19.
445 Karkaria, U. Automotive News. BMW hatches an EV battery with 30% more range. Dec. 01, 2022. Available at: https://www.autonews.com/mobility-report/bmws-next-generation-ev-battery-offers-30-more-range. (Accessed: Dec. 6, 2023).
446 Karkaria, U. Automotive News. 202 Volvo EVs get rear-wheel drive, longer range. Available at: https://www.autonews.com/cars-concepts/volvo-evs-have-e-motor-developed-house. (Accessed: Dec. 6, 2023).
447 Bloomberg New Energy Finance. Lithium-Ion Battery Pack Prices Hit Record Low of $139/kWh. Nov. 26, 2023. Available at: https://about.bnef.com/blog/lithium-ion-battery-pack-prices-hit-record-low-of-139-kwh/. (Accessed: Nov. 29, 2023).
448 2023 EPA Automotive Trends Report, at 64.
449 Bloomberg New Energy Finance. Lithium-Ion Battery Pack Prices Hit Record Low of $139/kWh. Nov. 26, 2023. Available at: https://about.bnef.com/blog/lithium-ion-battery-pack-prices-hit-record-low-of-139-kwh/. (Accessed: Dec. 6, 2023).
450 Abhirup, R.,Klayman, B. 2023. Reuters. Tesla joins GM, Ford in slowing EV factory ramp as demand fears spread. Available at: https://www.reuters.com/article/autos-electric-demand/tesla-joins-gm-ford-in-slowing-ev-factory-ramp-as-demand-fears-spread-idUSL4N3BP06X. (Accessed: Apr. 1, 2024).
451 Karkaria, U. 2024 Automotive News. Nissan to offshore next-gen Leaf EV production. Available at: https://www.autonews.com/manufacturing/nissan-offshore-next-gen-leaf-ev-production-sources. (Accessed: Apr. 1, 2024).
452 2023 EPA Automotive Trends Report, at 61, Figure 4.15.
453 DOE. Alternative Fuels Data Center. Hydrogen Refueling Infrastructure Development. Available at: https://afdc.energy.gov/fuels/hydrogen_infrastructure.html. (Accessed: Feb. 9, 2024).

As we discuss in Chapter 2.3, certain technologies' effectiveness for reducing fuel consumption requires optimization through the appropriate sizing of the powertrain. Autonomie uses sizing control algorithms based on data collected from vehicle benchmarking,[454] and the modeled electrification components are sized based on the performance neutrality considerations discussed in Chapter 2.3. This analysis iteratively minimizes the size of the powertrain components to maximize efficiency while enabling the vehicle to meet multiple performance criteria. The Autonomie simulations use a series of resizing algorithms that contain "loops," such as the acceleration performance loop (0-60 mph), which automatically adjusts the size of certain powertrain components until a criterion, like the 0-60 mph acceleration time, is met. As the algorithms examine different performance or operational criteria that must be met, no single criterion can degrade; once a resizing algorithm completes, all criteria will be met, and some may be exceeded as a necessary consequence of meeting others.

As discussed in Chapter 2.3, Autonomie applies different powertrain sizing algorithms depending on the type of vehicle considered because different types of vehicles not only contain different powertrain components to be optimized, but they must also operate in different driving modes. While the CONV sizing algorithm must consider only the power of the engine, the more complex algorithm for hybridized powertrains must simultaneously consider multiple factors, which could include the engine power, electric machine power, battery power, and battery capacity. Also, while the resizing algorithm for all vehicles must satisfy the same performance criteria, the algorithm for some electric powertrains must also allow those electrified vehicles to operate in certain driving cycles, like the US06 cycle, without assistance of the combustion engine and ensure the electric motor/generator and battery can handle the vehicle's regenerative braking power, all-electric mode operation, and intended range of travel.

To establish the effectiveness of the technology packages, Autonomie simulates the vehicles' performance on compliance test cycles, as discussed in Chapter 2.3.[455,456,457] For vehicles with CONVs and micro hybrid powertrains, Autonomie simulates the vehicles using the 2-cycle test procedures and guidelines.[458] For mild HEVs and strong HEVs, Autonomie simulates the same 2-cycle test, with the addition of repeating the drive cycles until the final SOC is approximately the same as the initial SOC, a process described in SAE J1711; SAE J1711 also provides test cycle guidance for testing specific to plug-in HEVs.[459] PHEVs have a different range of modeled effectiveness during "standard setting" CAFE Model runs, in which the PHEV operates under a "charge sustaining" (gasoline-only) mode – similar to how SHEVs function – compared to "EIS" runs, in which the same PHEV operates under a charge depleting mode – similar to how BEVs function. For BEVs and FCEVs, Autonomie simulates vehicles performing the test cycles per guidance provided in SAE J1634.[460]

The range of effectiveness for the electrification technologies in this analysis is a result of the interactions between the components listed above and how the modeled vehicle operates on its respective test cycle. This range of values will result in some modeled effectiveness values being close to real-world measured values, and some modeled values that will depart from measured values, depending on the level of similarity between the modeled hardware configuration and the real-world hardware and software configurations. This modeling approach comports with the National Academy of Science 2015 recommendation to use full vehicle modeling supported by the application of lumped improvements at the sub-model level.[461] This approach allows for the isolation of sub-model technology effects on the full-vehicle model output, which supports a higher degree of accuracy and specificity in electrification component selection within the model. The details of the approach are discussed further in section 3.3.4.1.

See Figure 3-23 and Figure 3-24 below for the standard-setting and unconstrained analyses, respectively, as well as for HDPUVs in Figure 3-25.

[454] Chapter "Vehicle Sizing Process" of the CAFE Analysis Autonomie Documentation.
[455] EPA. 2023. How Vehicles are Tested. Available at: https://www.fueleconomy.gov/feg/how_tested.shtml. (Accessed: Feb. 7, 2024).
[456] Chapter "Test Procedure and Energy Consumption Calculations" of the CAFE Analysis Autonomie Documentation.
[457] EPA. 2017. EPA Test Procedure for Electric Vehicles and Plug-in Hybrids. DRAFT Summary. Available at: https://fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf. (Accessed: Feb. 9, 2024).
[458] 40 CFR part 600.
[459] PHEV testing is broken into several phases based on SAE J1711 charge-sustaining on the city and HWFET cycle, and charge-depleting on the city and HWFET cycles.
[460] SAE J1634. Battery Electric Vehicle Energy Consumption and Range Test Procedure. July 12, 2017.
[461] 2015 NAS report, at 292.

Figure 3-23: Light-Duty Electrification Technology Effectiveness Values for All Vehicle Technology Classes (Standard Setting)

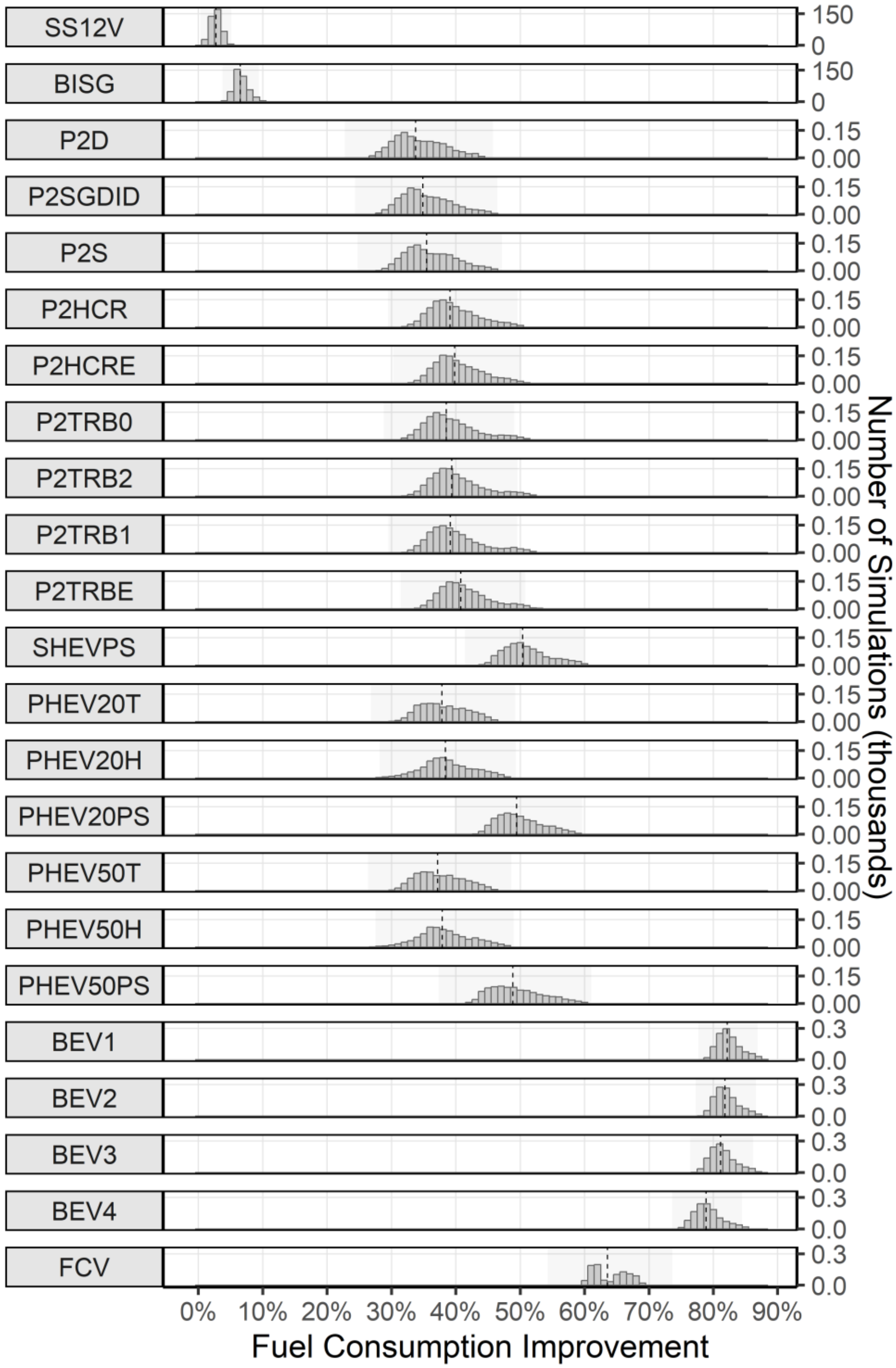


Figure 3-24: Light-Duty Electrification Technology Effectiveness Values for All Vehicle Technology Classes (Unconstrained)

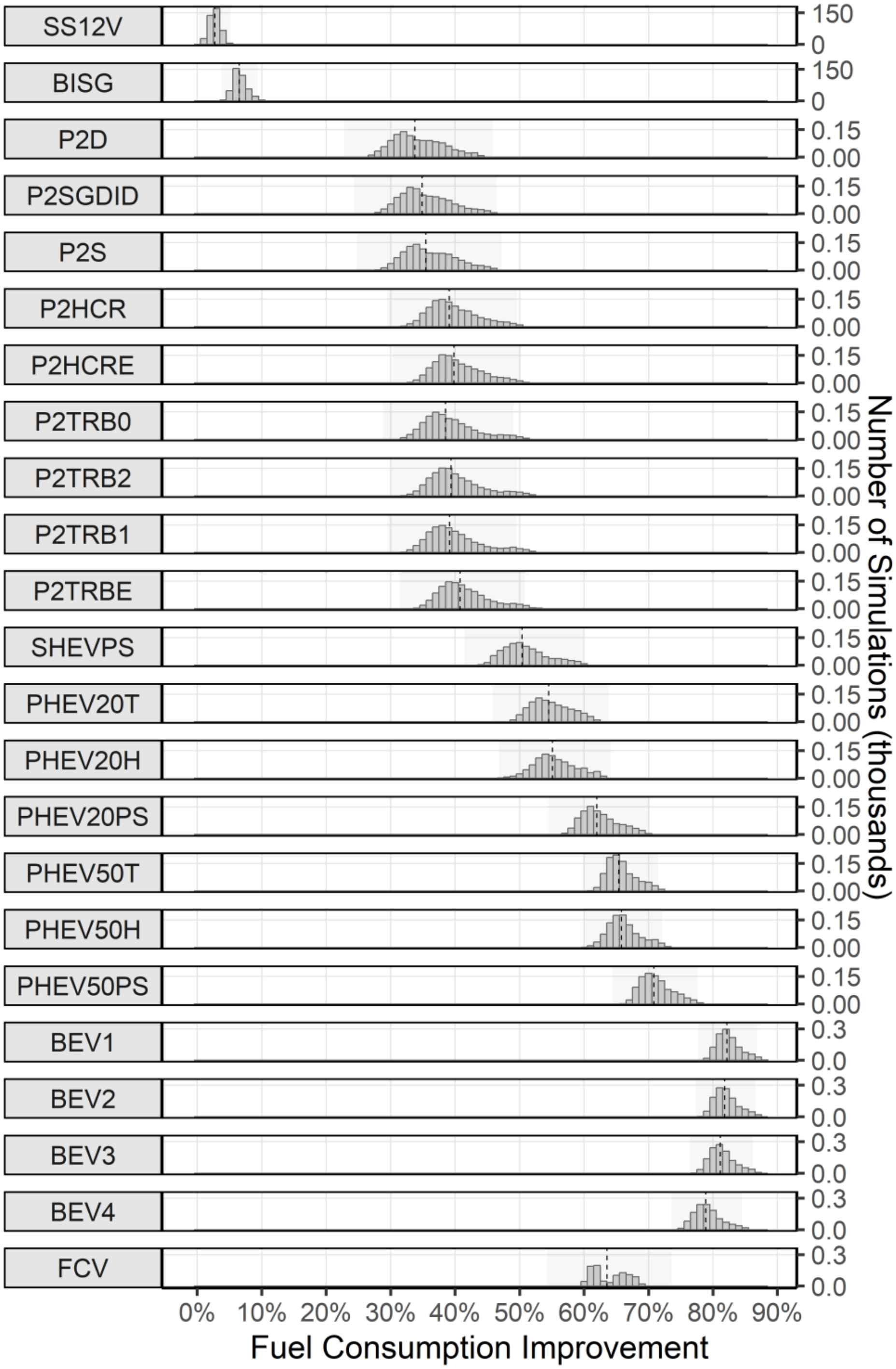
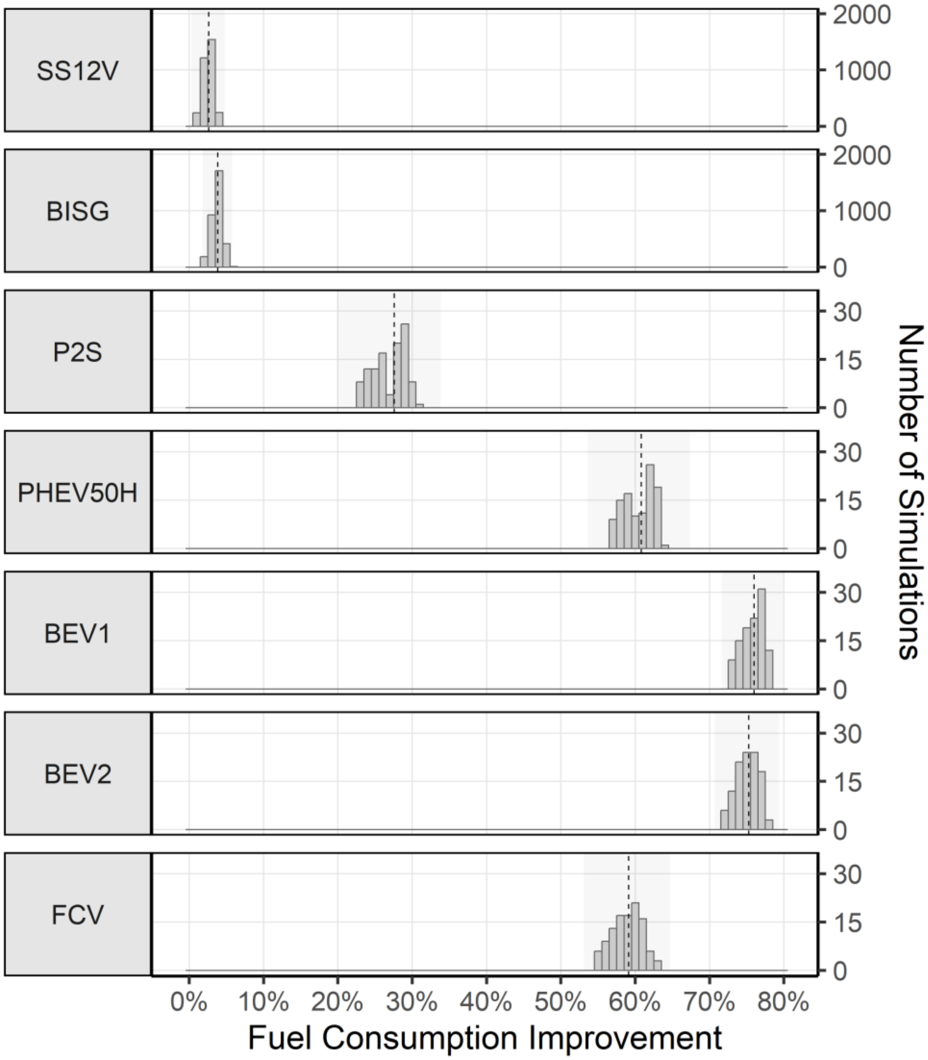


Figure 3-25: Heavy-Duty Pick-up and Van (HDPUV) Electrification Technology Effectiveness Values for All Vehicle Technology Classes



The following subchapters discuss the data that we use to model each electrification component and the Autonomie models that we use to simulate the effectiveness of each electrified powertrain technology on its respective test cycle.

3.3.4.1. Batteries, Electric Motor/Generators, Power Electronics, and Accessories

Autonomie determines the effectiveness of each electrified powertrain type (for light-duty vehicles as well as heavy-duty pickups and vans) by modeling the basic components, or building blocks, for each powertrain, and then combining the components modularly to determine the overall efficiency of the entire powertrain. The basic building blocks that comprise an electrified powertrain in the analysis include the battery, electric motor/generators, power electronics, and accessory loads.

Autonomie identifies components for each electrified powertrain type and then interlinks those components to create a powertrain architecture. Autonomie then models each electrified powertrain architecture and provides an effectiveness value for each architecture. For example, Autonomie determines a BEV’s overall efficiency by considering the efficiencies of the battery, the electric traction drive system (the electric machine and power electronics), and mechanical power transmission devices. Or, for a SHEVP2, Autonomie combines a very similar set of components to model the electric portion of the hybrid powertrain in addition to the combustion engine, transmission, and related powertrain and components.

For this analysis, Autonomie employs a set of electric motor efficiency maps created by Oak Ridge National Laboratory (ORNL): one for a traction motor and an inverter, the other for a motor/generator and inverter.[462] Autonomie also uses test data validations from technical publications to determine the peak efficiency of BEVs and FCEVs. The electric motor efficiency maps, created from production vehicles as shown in Table 3-74 below, represent electric motor efficiency as a function of torque and motor revolutions per minute (RPM). These efficiency maps provide nominal and maximum speeds, as well as a maximum torque curve. Argonne uses the maps to determine the efficiency characteristics of the motors, which includes some of the losses due to power transfer through the electric machine.[463] Specifically, Argonne scales the efficiency maps, specific to powertrain type, to have total system peak efficiencies ranging from 96-98 percent[464] – such that their peak efficiency value corresponds to the latest state-of-the-art technologies, as opposed to retaining dated system efficiencies (90-93 percent).[465] Table 3-74 also shows the electric machine efficiency map sources for the different light-duty and HDPUV powertrain configurations that we use in this analysis.

Table 3-74: Electric Machine Efficiency Map Sources for Different Powertrain Configurations

Powertrain Type	Vehicle Class	Source of Efficiency Map for Motor1 (Traction Motor) + Inverter	Source of Efficiency Map for Motor2 (Motor/Generator) + Inverter
SS12V	LD & HDPUV	Camry HEV EM1 data from ORNL	
BISG	LD & HDPUV	Camry HEV EM1 data from ORNL	
SHEVP2	LD & HDPUV		Sonata HEV EM2 data from ORNL
SHEVPS, PHEV20	LD	Camry HEV EM1 data from ORNL	Camry HEV EM2 Data from ORNL
PHEV50	LD	Camry HEV EM1 data from ORNL	Sonata HEV EM2 Data from ORNL
	HDPUV		
BEV and FCEV	LD	Chevrolet Bolt EM data from SAE paper[52]	
	HDPUV	EM data from Borg Warner[466]	

Beyond the powertrain components, Autonomie also considers electric accessory devices that consume energy and affect overall vehicle effectiveness. This includes headlights, radiator fans, wiper motors, engine control units (ECU), transmission control units (TCU), cooling systems, and safety systems. In real-world driving and operation, the electrical accessory load on the powertrain varies depending on how the driver uses certain features and the condition in which the vehicle is operating, such as for night driving or hot weather driving. However, for regulatory test cycles related to fuel economy, the electrical load is repeatable because the fuel economy regulations control for these factors, as discussed in Chapter 2.3.[467] Accessory loads during test cycles do vary by powertrain type and vehicle technology class, since distinctly different powertrain components and vehicle masses will consume different amounts of energy.

The analysis fleets consist of different vehicle types with varying accessory electrical power demand. For instance, vehicles with different motor and battery sizes will require different sizes of electric cooling pumps

[462] Oak Ridge National Laboratory. 2008. Evaluation of the 2007 Toyota Camry Hybrid Synergy Drive System. Submitted to the U.S. Department of Energy; Oak Ridge National Laboratory. 2011. Annual Progress Report for the Power Electronics and Electric Machinery Program.
[463] See CAFE Analysis Autonomie Documentation, chapter titled 'Electric Machine Efficiency Maps'.
[464] See CAFE Analysis Autonomie Documentation, chapter titled 'Electric Machine Peak Efficiency Scaling'.
[465] Burress, T.A. et al. 2008. Evaluation of the 2007 Toyota Camry Hybrid Synergy Drive System. Oak Ridge National Laboratory. ORNL/TM-2007/190. Available at: https://www.osti.gov/biblio/928684/. (Accessed: Dec. 6, 2023); Oak Ridge National Laboratory. ORNL/TM-2011/263. Available at: https://digital.library.unt.edu/ark:/67531/metadc845565/m2/1/high_res_d/1028161.pdf. (Accessed:Feb. 9, 2024).
[466] BorgWarner. HVH410-075 Electric Motor. June 12, 2023. Available at: https://www.cascadiamotion.com/images/catalog/remy-pds---hvh410-075-sheet-euro-pr-3-16__5_.pdf. (Accessed: Feb. 9, 2024).
[467] NHTSA Benchmarking. Laboratory Testing of a 2017 Ford F-150 3.5 V6 EcoBoost with a 10-speed transmission. DOT HS 812 520.

and fans to optimally manage component temperatures. Autonomie has built-in models that can simulate these varying subsystem electrical loads. However, for this analysis, we use a fixed, constant power draw (by vehicle technology class and powertrain type) to represent the effect of these accessory loads on the powertrain on the 2-cycle test. We intend and expect that fixed accessory load values will, on average, have similar impacts on effectiveness as found on actual manufacturers' systems. This process is in line with the past analyses.[468,469] For this analysis, we aggregate electrical accessory load modeling assumptions for the different powertrain types (electrified and conventional) and classes (both light-duty and HDPUV) from data from the Draft TAR, EPA Proposed Determination,[470] data from manufacturers,[471] research and development data from DOE's Vehicle Technologies Office,[472,473,474] and DOT-sponsored vehicle benchmarking studies completed by Argonne's AMTL, with vehicles such as the Toyota RAV4 Prime,[475] Nissan Leaf,[476] and Chevy Bolt.[477] These assumptions are provided below in Table 3-75.[478]

Table 3-75: Accessory Load Assumptions in Watts by Vehicle Class and Powertrain Type

Vehicle Class	Performance Category	Accessory Load (Watts) by Vehicle Powertrain Type			
		CONVs	HEVs	PHEVs	BEVs
Compact	LD Base	250	275	275	225
Compact	LD Premium	300	325	325	275
Midsize	LD Base	250	275	275	225
Midsize	LD Premium	300	325	325	275
Small SUV	LD Base	275	300	300	250
Small SUV	LD Premium	325	350	350	300
Midsize SUV	LD Base	275	300	300	250
Midsize SUV	LD Premium	325	350	350	300
Pickup	LD Base	275	300	300	250
Pickup	LD Premium	325	350	350	300
Heavy-Duty Pickup	HDPUV	1,000	1,000	1,000	1,000
Heavy-Duty Van	HDPUV	1,000	1,000	1,000	1,000

The following subchapters discuss how the assumptions for each powertrain type are simulated across the test cycle to meet modeling and performance requirements.

3.3.4.2. Micro Hybrids

Autonomie represents a micro hybrid system using SS12V technology, which assumes that this powertrain type is not capable of providing any brake energy recovery. The effectiveness improvement from SS12V

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468 Technical Assessment Report. July 2016. Chapter 5.
469 EPA Proposed Determination TSD. November 2016, at 2–270.
470 EPA Proposed Determination TSD. November 2016, at 2–270.
471 Alliance of Automobile Manufacturers Comments on Draft TAR, at 30.
472 DOE Electric Drive Systems Research and Development. Office of Energy Efficiency & Renewable Energy (EERE). Available at: https://www.energy.gov/eere/vehicles/vehicle-technologies-office-electric-drive-systems. (Accessed: Feb. 9, 2024).
473 Argonne National Laboratory. 2023. Advanced Mobility Technology Laboratory (AMTL). Available at: https://www.anl.gov/es/advanced-mobility-technology-laboratory. (Accessed: Feb. 9, 2024).
474 DOE's lab years are ten years ahead of manufacturers' potential production intent (e.g., 2020 Lab Year correlates with vehicle model year 2030).
475 Iliev, S. et al. 2022. Vehicle Technology Assessment, Model Development, and Validation of a 2021 Toyota RAV4 Prime. Report No. DOT HS 813 356. National Highway Traffic Safety Administration.
476 Jehlik, F. et al. 2022.
Vehicle Technology Assessment, Model Development, and Validation of a 2019 Nissan Leaf Plus. Report No. DOT HS 813 352. National Highway Traffic Safety Administration.
477 Jehlik, F. et al. 2022. Vehicle Technology Assessment, Model Development, and Validation of a 2020 Chevrolet Bolt. Report No. DOT HS 813 351. National Highway Traffic Safety Administration.
478 See ANL - Summary of Main Component Performance Assumptions_NPRM_2206 and ANL - All Assumptions_Summary_NPRM_2206.xlsx which can be found in the rulemaking docket by filtering for Supporting & Related Materials.

systems is attributable to the amount of fuel saved during the engine idling period on the 2-cycle test. Although the SS12V system only provides minimal benefit on the 2-cycle test,[479] the fuel economy improvement from SS12V systems is also credited in the analysis through the application of OC FCIVs. For further discussion of the SS12V system models, see the CAFE Analysis Autonomie Documentation.[480]

Micro hybrid systems normally do not provide propulsion assist, so this technology has little to no impact on the vehicle performance metrics. Thus, in this analysis, Autonomie does not resize the powertrain – whether light-duty or HDPUV – when a vehicle adopts a micro hybrid system because with or without the micro hybrid system, the combustion engine size must be retained to maintain performance metrics, such as acceleration.

3.3.4.3. Mild Hybrids

The mild hybrid system in Autonomie is a 48V BISG and can be applied to both light-duty and HDPUV fleet vehicles.[481] Mild hybrid vehicles provide idle-stop function and capture some regenerative braking energy; although mild hybrids can also provide some assistance to the engine during the initial propelling of the vehicle, this is done to improve efficiency and does not significantly improve acceleration performance. With BISG mild hybrids, the electric machine is linked to the engine through a belt, and the potential power assistance is usually limited. In the light-duty analysis, a BISG system uses a 10-kW motor/generator paired with a 403 Wh battery pack to best approximate mild hybrid systems found in the marketplace.[482] For the HDPUVs, we used a 517 Wh battery pack. The specification of this system is provided in the Autonomie Input and Assumptions Description Files.[483]

Like the modeled micro hybrid system, the effectiveness improvement from the mild hybrid system is attributable to the amount of fuel saved during the engine idling period on the 2-cycle test, and additional fuel economy benefits are credited through the application of OC FCIVs. Also, similar to the micro hybrid system, Autonomie does not resize the vehicle powertrain with the addition of the 48V BISG technology. However, the mild hybrid model allows limited assist to propel the vehicle and limited regenerative braking.

3.3.4.4. Strong Hybrids

As discussed earlier, this analysis considers two types of strong hybrid technology: A series-parallel power-split hybrid (SHEVPS) architecture and a parallel hybrid (SHEVP2) architecture. The SHEVPS model in Autonomie includes a power-split device, two electric machines, and an engine, and allows for various interactions between these components; only light-duty vehicles are modeled with this technology. The SHEVP2 model in Autonomie is based on the pre-transmission (P2) configuration where the electric motor is placed between the engine and transmission for direct flow of power to the wheels. The vehicle is propelled either by the combustion engine, the electric motor, or both simultaneously, but the speed/efficiency region of operation for SHEVP2s under any engine/motor combination is ultimately dictated by the transmission gearing and speed. Both light-duty and HDPUVs are simulated using P2 hybrid architectures. A detailed discussion of the SHEVPS and SHEVP2 modeling and validation are provided in the CAFE Analysis Autonomie Documentation.[484] Autonomie full vehicle models representing the strong hybrids are based on vehicle test data from vehicle benchmarking.

As discussed previously in this subchapter, power-split hybrids utilize a full-time Atkinson mode engine, two electric machines, and a planetary gear set transmission along with a battery pack to propel the vehicle. The smaller motor/generator (EM2) is used to control the engine speed and the engine (ICE) is used to either charge the battery or to supply additional electric power to the second "drive" motor. The more powerful drive ("traction") motor/generator (EM1) is permanently connected to the vehicle's final drive and always turns with

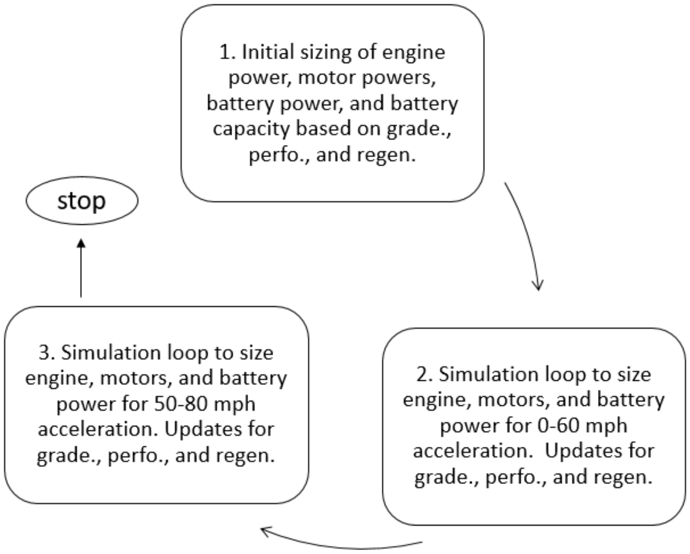
[479] The regulatory two-cycle test only contains 18 percent vehicle idling, which is not always representative of real-world operation. See EPA Detailed Test Information. Available at: https://www.fueleconomy.gov/feg/fe_test_schedules.shtml. (Accessed: Feb. 9, 2024).
[480] See Chapters "Electric Machines Efficiency Maps" and "Conventional Powertrain (Conventional/Micro-12V/Mild Hybrid BSIG)" of the CAFE Analysis Autonomie Documentation.
[481] These systems are 48V Direct Current (DC) electrical systems.
[482] Colwell, K.C. 2019. The 2019 Ram 1500 eTorque Brings Some Hybrid Tech, If Little Performance Gain, to Pickups. Car and Driver. Last revised: Mar. 14, 2019. Available at: https://www.caranddriver.com/reviews/a22815325/2019-ram-1500-etorque-hybrid-pickup-drive. (Accessed: Feb. 9, 2024).
[483] See ANL – Summary of Main Component Performance Assumptions_NPRM_2206 and ANL – All Assumptions_Summary_NPRM_2206.xlsx which can be found in the rulemaking docket by filtering for Supporting & Related Materials.
[484] CAFE Analysis Autonomie Documentation, Chapters titled 'Power-Split HEV (Split HEV)', 'Autonomie Validatoin'.

the wheels. The Autonomie SHEVPS model and controls are based on a few high-level characteristics of real-world strong hybrid power-split systems that drive how the components are sized to meet performance metrics. For example:

- In the initial vehicle launch, when SOC is stable, the electric motor is the only propulsion component utilized; and
- In normal city driving, the engine could both propel the vehicle and (via the electric motor/generator) charge the battery.

The SHEVPS resizing algorithm makes an initial estimate of the size of the engine, battery, and electric motor/generators. The initial estimates for the ICE and EM1 sizes are based on the peak power required for acceleration performance and the continuous power required for gradeability performance. The initial estimates for the battery and EM2 power is based on the maximum regenerative braking power. With these initial size estimates, the algorithm computes the vehicle mass and runs simulations to determine if 0-60 and 50-80 mph acceleration performance is acceptable. If acceleration is not satisfactory (too fast or too slow), the algorithm iteratively adjusts the sizes of the engine, electric motors, and battery and runs simulations until a minimum powertrain size is found that meets all performance requirements. With each iteration, characteristics of the engine, battery, and electric motor/generators are also updated for gradeability performance and regeneration, if necessary. Figure 3-26 below shows the general steps of the SHEVPS sizing algorithm. Detailed descriptions are available in the CAFE Analysis Autonomie Documentation.

Figure 3-26: Simplified SHEVPS Sizing Algorithm in Autonomie

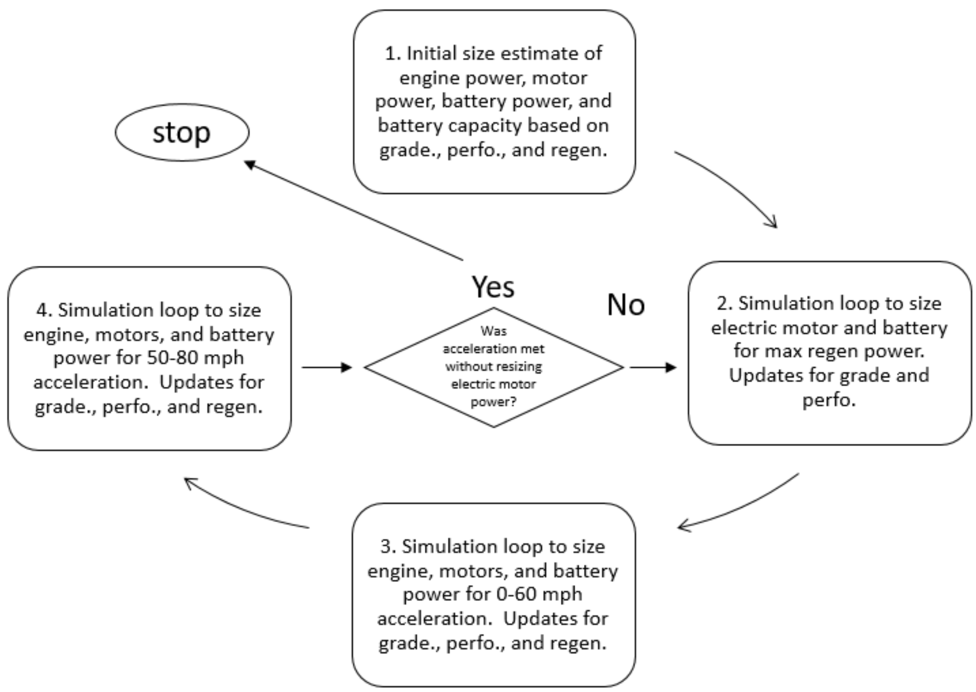


The SHEVP2 uses a combustion engine and a multi-speed transmission-integrated electric motor (EM1). As discussed earlier, this SHEVP2 allows most engines and advanced speed transmissions to integrate with an electric motor. To minimize the number of Autonomie simulations for combinations of engines and transmissions for all 14 vehicle classes in both the light-duty and HDPUV analyses,[485] we use the AT8L2 as the only transmission that can be integrated with SHEVP2. As manufacturers have continued to increase gear counts from the common five and six speed gears while improving transmission internals, these modern improvements are carried into the SHEVP2 architecture. In model year 2022, about 50 percent of the light-duty fleet had transmissions with seven gears or higher.[486] Additionally, the higher-geared eight speed AT enables the maximization of engine efficiency by allowing the engine to operate in the more efficient region as compared to a lower geared transmission. These benefits are further discussed in Chapter 3.2.

[485] For this analysis, there are over 150,000 simulation results for all fourteen vehicles classes. That number does not include the simulations associated with sizing of components for different powertrains.
[486] See Chapter 3.2.2 for a more detailed breakdown of transmission penetration rates.

As with SHEVPS, the SHEVP2 resizing algorithm starts by estimating the size of the engine, battery, and motor/generator based on performance criteria or an estimated regenerative braking power, and then by calculating the associated vehicle mass. The algorithm then uses a simulation loop to find a more precise value of regenerative braking power generated in the Urban Dynamometer Driving Schedule (UDDS) "city driving" cycle and adjusts the motor/generator size and vehicle mass accordingly. Next, the algorithm uses simulation loops to optimize the engine, electric motor, and battery sizes in relation to acceleration performance criteria. If the acceleration criteria require downsizing the powertrain, the motor/generator size is not reduced as this would not be suitable to handle regenerative braking power. If the acceleration criteria cause the motor/generator to increase in size, the algorithm then returns to the regenerative braking loop and subsequently all other loops until all components are optimized. Figure 3-27 below shows a simplified sizing algorithm for SHEVP2s.

Figure 3-27: Simplified SHEVP2 Sizing Algorithm in Autonomie



To maintain performance neutrality, the acceleration optimization loops in the SHEVP2 algorithm differ between the non-performance vehicle class and the performance class. For performance classes, Autonomie does not resize the powertrain to avoid reducing the performance in SHEVP2 hybrids compared to the same vehicle with a CONV. This mimics the observed marketplace trend in which parallel hybrid models tend to retain a similar engine size as the non-hybrid models bearing the same nameplate.[487,488] For non-performance classes, SHEVP2 powertrains allow engine downsizing. This algorithm is discussed in the CAFE Analysis Autonomie Documentation with a more detailed flow chart of the closed loop design.[489]

In addition, we limit adoption of some advanced engine technologies with strong hybrids in cases where the electrification technology would have little effectiveness benefit beyond the benefit of the advanced engine system but would substantially increase costs. Specifically, we do not model strong hybrid technologies with VCR engines and eVTG engines. We believe that manufacturers would not consider these combinations because the combination of electrification and advanced engine technologies are not as cost-effective as other technologies.

487 For example, the 2022 4WD Ford F-150 uses a turbo-charged 3.5L engine for its hybrid and is an option for its non-hybrid model.
488 For example, the 2022 Hyundai Elantra uses a turbo-charged 1.6L engine for its hybrid and is an option for its non-hybrid model.
489 Chapter "Vehicle Sizing Process" of the CAFE Analysis Autonomie Documentation.

3.3.4.5. Plug-in Hybrids

The effectiveness of the PHEV systems is dependent on both the vehicle's battery pack size and range, in addition to the other fuel economy-improving technologies on the vehicle (e.g., aerodynamic and MR technologies).

As discussed earlier in Chapter 3.3.1, Autonomie follows EPA regulatory guidance using the SAE J1711 test procedure to model the incremental effectiveness of adding PHEV technology to a vehicle. The procedure from this guidance is divided into several phases that model "charge sustaining", "charge depleting", and "cold operation" calculations for different test cycles. This is described in detail in the CAFE Analysis Autonomie Documentation.[490]

The resizing algorithm for PHEVs considers the power needed for acceleration performance and all-electric mode operation; the PHEV resizing algorithms use these metrics for an initial estimation of engine, motor(s), and battery power, as well as battery capacity. The initial mass of the vehicle is then computed, including the weight for a larger battery pack and charging components.[491] However, since PHEVs offer expanded electric driving capacity, their resizing algorithm must also yield a powertrain with the ability to achieve certain driving cycles and range in electric only mode, in which the engine remains off for all or most the operation. The analysis sizes the PHEV motor/generator and battery power so that the vehicle can complete either the city cycle UDDS or US06 (aggressive, high speed) driving cycle in electric mode, and the battery energy storage capacity to achieve the specified AER on the 2-cycle tests on the basis of adjusted energy values.[492,493]

For this analysis, we classify PHEVs into six technology levels, as discussed previously: (1) PHEV20PS indicating a vehicle with an AER of 20 miles and powertrain system based on SHEVPS hybrid architecture; (2) PHEV50PS indicating a vehicle with an AER of 50 miles and powertrain system based on SHEVPS hybrid architecture; (3) PHEV20T indicating a vehicle with an AER of 20 miles and powertrain system based on a turbo-charged SHEVP2 hybrid architecture; (4) PHEV50T indicating a vehicle with AER of 50 miles and powertrain system based on a turbo-charged SHEVP2 hybrid architecture; (5) PHEV20H indicating a vehicle with an AER of 20 miles and an HCR engine utilizing a SHEVP2 architecture; and (6) PHEV50H indicating a vehicle with AER of 50 miles and an HCR engine utilizing a SHEVP2 architecture. While light-duty PHEVs are modeled with all six of these PHEV architectures, HDPUV PHEVs are only modeled with the PHEV50H architecture for reasons discussed in Chapter 3.3.1.

The PHEV20 and PHEV50 resizing algorithms are functionally equal and differ only in the type of electric mode driving cycle simulated in each (UDDS for PHEV20PS/20T/20H, or US06 for PHEV50PS/50T/50H). These algorithms simulate the driving cycles in an iterative loop to determine the size of the motor/generators and the battery required to complete the cycles. In the case of PHEV20PS/20T/20H, the power of the motor/generators and battery must be sized to propel the vehicle through the UDDS cycle in "charge-depleting (CD) mode"; in this mode, the electric machine alone propels the vehicle except during high power demands, at which point the engine may turn on and provide propulsion assistance. The PHEV50PS/50T/50H motor(s) and battery must be sized to power the vehicle through the US06 cycle in "EV mode," where the engine is always off. Then, all PHEV algorithms adjust the battery capacity, or vehicle range, by ensuring the battery energy content is sufficient to complete a simulated UDDS + Highway Fuel Economy Test (HWFET) combined driving cycle, based on EPA-adjusted energy consumption. Finally, the algorithm sizes the engine, motor/generator(s), and battery power accordingly to meet 0-60 and 50-80 mph acceleration targets. All loops are repeated until the acceleration targets are met without needing to resize the motor/generators, at which point the resizing algorithm finishes. Figure 3-28 below shows the general steps of the PHEV sizing algorithm. Detailed steps can be seen in the CAFE Analysis Autonomie Documentation.[494]

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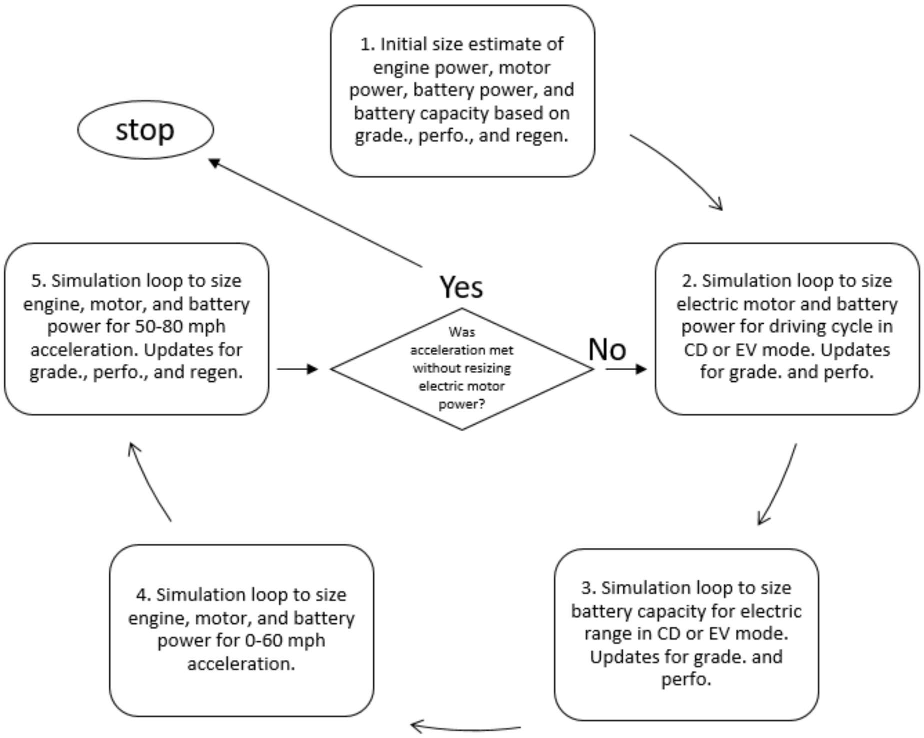
[490] Chapter "Vehicle Sizing Process" of the CAFE Analysis Autonomie Documentation.
[491] CAFE Analysis Autonomie Documentation, titled '9.3.1.3 Parallel HEV (Par HEV) Sizing Algorithm'.
[492] Battery sizing and the definition of the combined 2-cycle test's AER is discussed in detail in Chapter titled 'Battery Performance and Cost Model (BatPaC)' of the CAFE Analysis Autonomie Documentation.
[493] Argonne has incorporated SAE J1711, Recommend Practice for Measuring Exhaust Emissions and Fuel Economy of Hybrid-Electric Vehicles, Including Plug-In Hybrid Vehicles, into the Autonomie modeling.
[494] CAFE Analysis Autonomie Documentation, Chapters titled 'Parallel PHEV Sizing Algorithm' and 'Voltec PHEV (Extended Range) Vehicle Sizing Algorithm'.

Figure 3-28: Simplified PHEV Sizing Algorithm in Autonomie



As discussed earlier, the Autonomie sizing algorithm is automated and any change in one of the component checks in the steps shown in Figure 3-29 requires the components to be revaluated and sized appropriately.

3.3.4.6. Battery Electric Vehicles

The effectiveness of BEVs – whether for the light-duty or HDPUV fleet – is dependent on the efficiency of the components that transfer power from the battery to the driven wheels. These components include the battery, electric machine, power electronics, and mechanical gearing. For this analysis, we use efficiency maps from production vehicles to calculate electric machine efficiency and area for which the maps operate and scale the electric machine efficiency such that the peak efficiency value corresponds to the latest state-of-the-art technologies. The range of a BEV in the analysis is dependent on the vehicle's class and the battery pack size.

An important note about Autonomie's BEV model is that it does not simulate any one manufacturer's technology, architecture, battery pack characteristics, or thermal management and state-of-charge control strategies. Those BEV characteristics are unique for each manufacturer's vehicle models. And, like many other parts of this analysis, these technology models in Autonomie are discrete representative designs. Accordingly, the absolute MPGe from Autonomie could vary significantly compared to production vehicles in the market in the rulemaking timeframe.[495]

Another important note about BEVs in this analysis is that the effectiveness of a BEV built in the CAFE Model is independent of the effectiveness of the CONV it replaces. As vehicles adopt BEV technology,[496] the CAFE Model uses the Autonomie databases to determine the added incremental efficiency that will bring a specific vehicle up to the appropriate fuel economy level that allows the manufacturer's fleet to achieve compliance. Since the CAFE Model considers a variety of vehicle types with differing powertrain types, vehicle technology classes, performance criteria, and physical properties (curb weight, etc.), each with a different overall

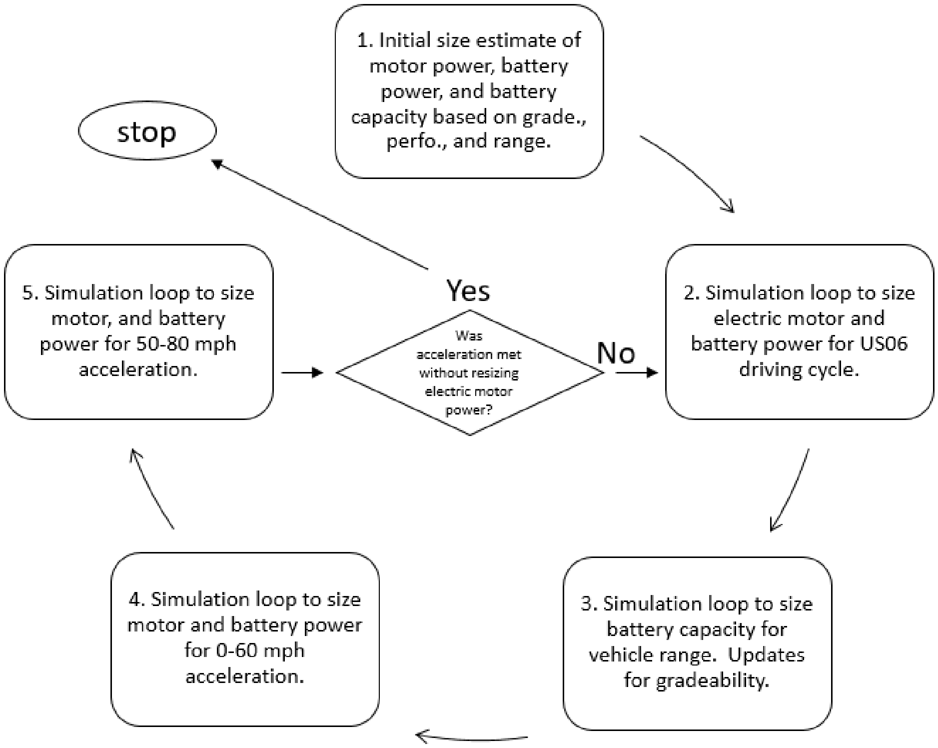
[495] Seredynski, P. 2013. Decoding Electric Car MPG: With Kilowatt-Hours, Small Is Beautiful. Edmunds. Last revised: Sept. 6th, 2013. Available at: https://www.edmunds.com/fuel-economy/decoding-electric-car-mpg.html. (Accessed: Feb. 9, 2024).
[496] Within standard setting years, BEV adoption is prohibited in response to increasing CAFE standards. However, for the purpose of our "real-world" analysis for the Environmental Impact Statement we do not apply the same restrictions.

effectiveness, the efficiency increment needed to achieve BEV effectiveness will vary with each case. The effectiveness used in the CAFE Model represents the difference between the performance of the full vehicle models' simulations — the full vehicle model representing the initial-state vehicle versus the full vehicle model representing the end-state — with all additional fuel economy-improving technology applied, as we discuss in Chapter 2.3.

As we discuss in Chapter 3.3.1, Autonomie follows EPA regulatory guidance using the SAE J1634 test procedure to determine incremental effectiveness for BEVs in the CAFE Model analysis; the procedure from this guidance uses the multi-cycle test (MCT) method from this SAE standard. Autonomie's BEV model starts with the battery at full charge or maximum SOC and simulates the vehicle on the MCT until the battery is empty or has reached a minimum SOC.[497]

The resizing algorithm for BEVs is functionally the same as the PHEV algorithm; however, BEVs do not use a combustion engine, and thus, the BEV algorithm does not include this component. The model calculates initial estimates of electric motor and battery powers based on acceleration performance, gradeability performance, and vehicle range. Then, the algorithm successively runs four simulation loops to finetune the powertrain size to ensure that all performance and operational criteria are maintained. First, the BEV electric motor and battery are sized to power the vehicle through the US06 cycle. Next, the battery capacity is adjusted to ensure the energy content is sufficient to complete a simulated UDDS+HWFET combined driving cycle, based on EPA adjustment factors to represent sticker values, and to meet the vehicle range requirement. Finally, the electric motor and battery powers are sized to meet 0-60 and 50-80 mph acceleration targets. If either acceleration simulation loop results in a change to the electric motor size, the algorithm repeats all simulation loops. The algorithm finishes once the acceleration targets are met without resizing the electric motor. Figure 3-29 below shows a simplified sizing algorithm for BEVs.

Figure 3-29: Simplified BEV Sizing Algorithm in Autonomie



For further detailed discussion of how Autonomie simulates BEVs, see the CAFE Analysis Autonomie Documentation.[498]

[497] The minimum and maximum SOC for BEVs in this analysis is 5 to 95 percent.
[498] Chapter "Vehicle Sizing Process" of the CAFE Analysis Autonomie Documentation.

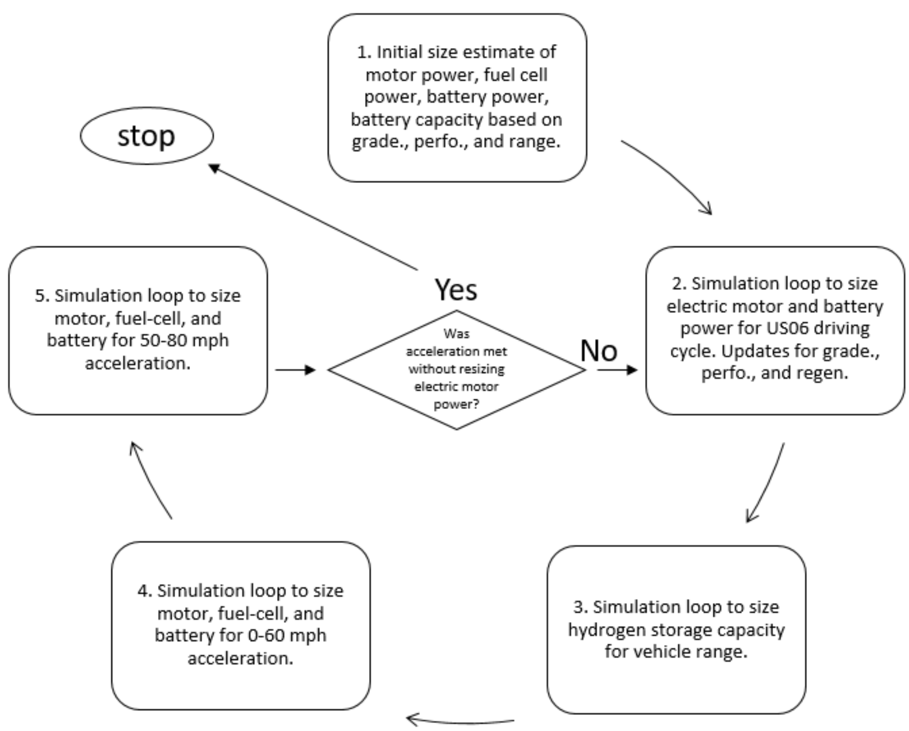
3.3.4.7. Fuel Cell Electric Vehicles

The fuel-cell system in the analysis is modeled to represent hydrogen consumption as a function of the produced power, assuming normal-temperature operating conditions with a peak system efficiency of 64 percent. The specific power used for the system is 860 W/kg for light-duty vehicles and 600 W/kg for HDPUV vehicles. The hydrogen storage technology selected is a high-pressure tank with a specific weight of 0.04 kg H_2/kg, sized to provide a 320-mile range on the 2-cycle test on the basis of adjusted energy values.

The sizing algorithm for FCEVs is similar to PHEVs and BEVs but is adapted for the specific components of a FCEV powertrain – the electric machine, fuel-cell, hydrogen (H_2) fuel tank, and battery pack. During very low power operation, the battery pack alone powers the motor/wheels, depleting the battery charge. At moderate driving loads, the fuel cell provides electrical power (generated by consuming stored H_2) to the electric motor and to charge the battery. Under heavy loads, both the fuel cell and battery deliver electric power to the electric motor.

To begin the FCEV sizing algorithm, the model calculates initial estimates of electric motor, fuel cell, and battery powers based on criteria for acceleration, gradeability, and vehicle range. The algorithm successively runs four simulation loops to finetune powertrain size, ensuring that all performance and operational criteria are maintained. First, the FCEV electric motor and battery are sized to power the vehicle through the US06 cycle. Next, the model adjusts the on-board mass of H_2 fuel, as well as the fuel tank mass, to ensure the vehicle can complete a simulated 2-cycle test and meet the range requirement. Finally, the algorithm sizes the electric motor and fuel cell powers accordingly to meet 0-60 and 50-80 mph acceleration targets. If either acceleration simulation loop results in a change to the electric motor size, the algorithm repeats all simulation loops. Once the acceleration targets are met without resizing the electric motor, the algorithm completes. Figure 3-30 below shows a simplified sizing algorithm for FCEVs.

Figure 3-30: Simplified FCEV Sizing Algorithm



3.3.5. Electrification Costs

The total cost to electrify a vehicle in this analysis is based on the vehicle's battery and non-battery electrification component costs and requirements, as well as the traditional powertrain components that must be updated or removed from the vehicle to build the electrified powertrain. This subchapter provides insight into how these costs were determined and how they are used in this analysis.

3.3.5.1. Base Year Battery Pack Costs and Modeling

We work collaboratively with the experts at ANL to generate battery costs using BatPaC — a model designed to calculate EV battery costs. Electric vehicle battery costs are dependent on factors such as the battery pack design, cell chemistry, and subsequent power and energy metrics required to meet performance specifications. Argonne uses BatPaC to create lookup tables for battery cost and mass that the Autonomie simulations reference when a vehicle receives an electrified powertrain. The BatPaC battery cost estimates are generated for a *base year*, being model year 2022 for the current analysis; the assumed BatPaC inputs, discussed below, fairly characterize the state of the market in model year 2022.

To reflect how battery costs could decrease over the timeframe considered in the analysis, we apply a learning rate to the BatPaC-generated direct manufacturing costs. Broadly, the learning rate that we apply to batteries reflects middle-of-the-road year-over-year improvements through model year 2035, and then learning continues at a shallower rate as battery technology is expected to mature. More information on battery learning rates can be found in Chapter 3.3.5.3, as the rest of this subsection, Chapter 3.3.5.1, focuses on base year battery costs only. The following subchapters discuss Argonne's process for generating base year battery pack direct manufacturing costs.

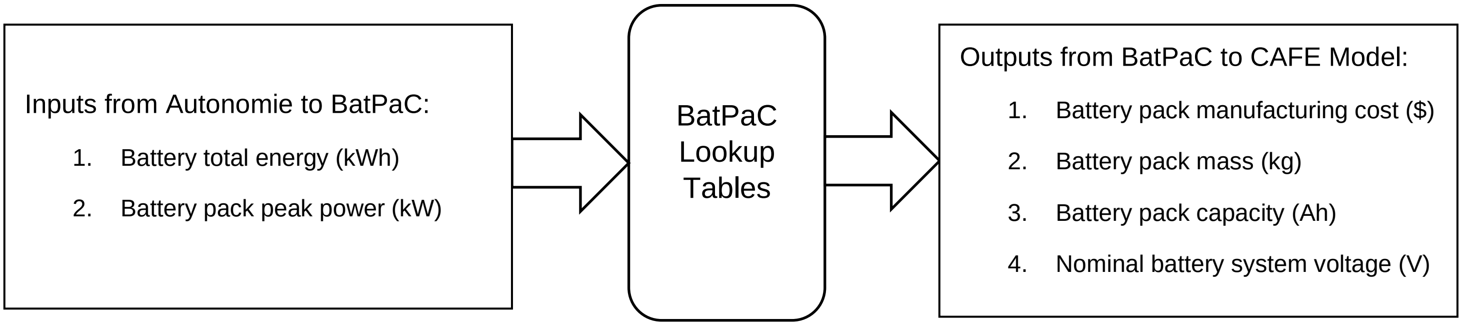
BatPaC is software designed for policymakers and researchers who are interested in estimating the manufacturing cost of lithium-ion batteries for electric drive vehicles.[499] The model provides data needed to design and build a battery pack, such as dimensions of the cell, estimate of materials, and manufacturing cost. The manufacturing costs are based on a "baseline plant" designed for a battery of intermediate size and production scale. A user can configure BatPaC with alternative chemistries, charging constraints, pack configurations, production volumes, and cost factors for other battery designs by customizing these parameters in the modeling tool. BatPaC calculations are based on a generic pack design that reasonably represents the weight and manufacturing cost of currently available automotive batteries. The advantage of using this approach is the ability to model a wide range of industry design specifications for various classes of vehicles.

For this analysis, we use BatPaC version 5.0 (March 2022 release) to estimate the base year battery cost for electrification technologies for both light-duty and HDPUV vehicles.[500] Similar to past rulemaking analyses, running individual BatPaC simulations for each full vehicle simulation requiring an electrified powertrain would have been computationally intensive and impractical, given that hundreds of thousands of simulated vehicles out of over a million simulated vehicles have an electrified powertrain. Accordingly, Argonne staff builds "lookup tables" with BatPaC to provide battery pack manufacturing costs, battery pack weights, and battery pack cell capacities for vehicles modeled in the large-scale simulation runs.

Figure 3-31 illustrates the inputs generated in Autonomie to create the BatPaC-based lookup tables, and the outputs characterized in the BatPaC-based lookup tables that are used to provide estimates referenced in this analysis. The peak power requirement or total energy requirement from the Autonomie simulations is used as an input to the BatPaC model, and outputs from the model include cell and pack costs, pack mass, pack capacity, and pack voltage.

[499] Argonne National Laboratory. BatPaC: Battery Manufacturing Cost Estimation. Available at: https://www.anl.gov/tcp/batpac-battery-manufacturing-cost-estimation. (Accessed: Feb. 9, 2024).
[500] Knehr, K. W. et al. 2022. Battery Performance and Cost Modeling for Electric-Drive Vehicles, Fourth Edition. Argonne National Laboratory. ANL/CSE-22/1. Available at: https://publications.anl.gov/anlpubs/2022/07/176234.pdf. (Accessed: Feb. 9, 2024). To request the BatPaC model used in this analysis, submit the request using the instructions at https://www.anl.gov/cse/batpac-model-software. (Accessed: Feb. 9, 2024).

Figure 3-31: Flowchart Showing How Autonomie Calls BatPaC Lookup Tables



While manufacturers' battery pack specifications are highly heterogeneous in the real world, we endeavor to develop battery pack costs that fairly encompass the cost of battery packs for vehicles in each technology class with a direct manufacturing cost (DMC) base year of model year 2022 (in 2021$). As detailed in the BatPaC model documentation, the costs of materials, labor, and capital equipment in the model are based on Argonne's estimates of 2021 values, "[t]hus, if BatPaC is used to calculate the current costs of batteries at current production levels (say 30,000 all-electric (BEV) packs per year) we expect it to provide good estimates of current battery prices to OEMs. Estimates done for ten years in the future should be at production levels of 100,000 to 500,000 units per year, which will result in lower pack prices because of the assumed increase in the degree of plant automation."[501]

We used EV and battery outlook reports,[502,503,504,505,506,507] vehicle teardown reports,[508,509] and stakeholder discussions[510] to determine most common battery pack chemistries for each modeled electrification technology. In addition, we looked at vehicle sales volumes[511] in model year 2022 to determine a reasonable base production volume assumption. The CAFE Analysis Autonomie Documentation details other specific assumptions that Argonne uses to simulate battery packs and their associated costs for the full vehicle simulation modeling, including updates to the battery management unit costs, and the range of power and energy requirements used to bound the lookup tables.[512] We discuss specific considerations for notable BatPaC specifications – battery cell cathode chemistry and plant production volume – in turn, below.

Applying learning curves to the battery pack DMC in subsequent analysis years lowers the cost such that the cost of a battery pack in any future model year could be representative of the cost to manufacture a battery pack; our assumptions for battery pack learning curves are discussed in detail in Chapter 3.3.5.3.

3.3.5.1.1. Battery Cell Chemistry

To determine which chemistries reasonably represent manufacturers' packs in model year 2022 for both light-duty and HDPUV vehicles, we worked with Argonne to survey industry trends, current and future battery cell chemistries, and vehicles in the A2Mac1 database – a widely used industry database that has component-

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[501] *Id*. at 1-2.
[502] Rho Motion. 2023. Seminar Series Live, Q1 2023 – Seminar Recordings. Emerging Battery Technology Forum. Available at: https://rhomotion.com/rho-motion-seminar-series-live-q1-2023-seminar-recordings. (Accessed: Dec. 7, 2023). Note that this seminar video is no longer publicly available to non-subscribers.
[503] Rho Motion. 2023. EV & Battery monthly & quarterly subscriptions. (Proprietary data).
[504] Benchmark Mineral Intelligence. 2023. Lithium-ion Batteries, Cathode, & Anode monthly & quarterly subscriptions. (Proprietary data).
[505] International Energy Agency. 2022. Global EV Outlook 2022 – Securing Supplies for an Electric Future. International Energy Agency. at 1-221. Available at: https://iea.blob.core.windows.net/assets/ad8fb04c-4f75-42fc-973a-6e54c8a4449a/GlobalElectricVehicleOutlook2022.pdf. (Accessed: Feb. 9, 2024).
[506] International Energy Agency. 2023. Global EV Outlook 2023 – Catching up with climate ambitions. International Energy Agency. at 1-142. Available at: https://iea.blob.core.windows.net/assets/dacf14d2-eabc-498a-8263-9f97fd5dc327/GEVO2023.pdf. (Accessed: Jan. 25, 2024).
[507] BloombergNEF. 2022. Electric Vehicle Outlook (EVO) 2022 and 2023. Available at: https://about.bnef.com/electric-vehicle-outlook/. (Accessed: Jan. 25, 2024).
[508] Hummel, P. et al. 2017. UBS Evidence Lab Electric Car Teardown – Disruption Ahead?. UBS. Available at: https://neo.ubs.com/shared/d1ZTxnvF2k. (Accessed: Feb. 12, 2024).
[509] A2Mac1: Automotive Benchmarking. (Proprietary data). Retrieved from https://portal.a2mac1.com/. (Accessed: Feb. 12, 2024).
[510] See Docket Submission of Ex Parte Meetings Prior to Publication of the Corporate Average Fuel Economy Standards for Passenger Cars and Light Trucks for Model Years 2027-2032 and Fuel Efficiency Standards for Heavy-Duty Pickup Trucks and Vans for Model Years 2030-2035 Notice of Proposed Rulemaking memorandum, which can be found under References and Supporting Material in the rulemaking Docket No. NHTSA-2023-0022.
[511] model year 2022 PMY Data See Chapter 2.2.1.1.
[512] Chapter "BatPac Lookup Tables" of the CAFE Analysis Autonomie Documentation.

level information of the vehicles in the marketplace[513] – in addition to other reports. The CAFE Analysis Autonomie Documentation includes more detail about the reports referenced for this analysis.[514] Table 3-76 shows the battery chemistries that we use by electrification technology for the base year battery pack costs in this analysis; note that, despite the recent emergence of diverging lithium chemistries between the light-duty and HDPUV fleets,[515,516] the battery chemistry is set to the same across light-duty and HDPUV vehicle applications due to the vehicles in production and information available at the time of the initial analysis.

Table 3-76: Base Year Battery Chemistries Assumed by Applications

Electrification Technology	Battery Chemistry
Mild HEV	LFP-G
Strong HEV	NMC622-G (Power Cell)
PHEV20	NMC622-G (Power Cell)
PHEV50	NMC622-G (Energy Cell)
BEV	NMC622-G (Energy Cell)

As discussed further in Chapter 3.3.5 below, for mild HEVs, we use the LFP-G[517] chemistry because power and energy requirements for mild hybrids are very low, the charge and discharge cycles (or need for increased battery cycle life) are high, and the battery raw materials are much less expensive than a nickel manganese cobalt (NMC)-based cell chemistry. We use NMC622-G[518] for all other electrified vehicle technology initial battery pack cost calculations.

While we made this decision at the time of modeling based on the best available information, while also considering feedback on prior rules,[519] more recent data affirms that EV batteries using NMC622 cathode chemistries are still a significant part of the market in model year 2022 and through model year 2023.[520,521,522] We recognize there is ongoing research and development with battery cathode chemistries that may have the potential to reduce costs and increase battery capacity.[523,524,525,526] In particular, we are aware of a recent shift by manufacturers to transition to lithium iron phosphate (LFP) chemistry-based battery packs as prices for materials used in battery cells fluctuate (see additional discussion below); however, we believe that based

[513] A2Mac1: Automotive Benchmarking. (Proprietary data). Retrieved from https://portal.a2mac1.com/. (Accessed: May 31, 2023).
[514] CAFE Analysis Autonomie Documentation, titled 'Cathode/Anode Combination Selection'.
[515] Karkaria, U. 2023. Mercedes Will Bring Electric Sprinter to U.S. This Year. Automotive News. Last revised: Feb. 7, 2023. Available at: https://www.autonews.com/cars-concepts/mercedes-esprinter-join-competition-us-year. (Accessed: Feb. 12, 2024).
[516] Iliff, L. 2023. Automotive News. Rivian won't join EV price battle thanks to 'robust' backlog. Available at: https://www.autonews.com/manufacturing/rivian-wont-join-ev-price-battle-thanks-robust-backlog. (Accessed: Apr. 1, 2024).
[517] Lithium Iron Phosphate ($LiFePO_4$) cathode and Graphite (G) anode.
[518] Lithium Nickel Manganese Cobalt Oxide ($LiNiMnCoO_2$) cathode and Graphite (G) anode.
[519] Stakeholders had commented on both the 2020 and 2022 final rules that batteries using NMC811 chemistry had either recently come into or were imminently coming into the market, and therefore we should have selected NMC811 as the appropriate chemistry for modeling battery pack costs.
[520] Rho Motion. Seminar Series Live, Q1 2023 – Seminar Recordings. Emerging Battery Technology Forum February 7, 2023. Available at: https://rhomotion.com/rho-motion-seminar-series-live-q1-2023-seminar-recordings. (Accessed: February 27, 2023). More specifically, the monthly weighted average global EV battery cathode chemistry across all vehicle classes shows a fairly even split. Even though we considered domestic battery production rather than global battery production for the analysis supporting this final rule, NMC622 is still prevalent even at a global level. Note that this seminar video is no longer publicly available to non-subscribers.
[521] Rho Motion. 2023. EV & Battery monthly & quarterly subscriptions. (Proprietary data).
[522] Benchmark Mineral Intelligence. 2023. Lithium-ion Batteries, Cathode, & Anode monthly & quarterly subscriptions. (Proprietary data).
[523] Slowik, P. et. al. 2022. Assessment of Light-Duty Electric Vehicle Costs and Consumer Benefits in the United States in the 2022-2035 Time Frame. International Council on Clean Transportation. Available at: https://theicct.org/wp-content/uploads/2022/10/ev-cost-benefits-2035-oct22.pdf. (Accessed: Apr. 9, 2024).
[524] Batteries News. 2022. Solid-State NASA Battery Beats The Model Y 4680 Pack at Energy Density by Stacking all Cells in One Case. Last revised: Oct. 20, 2022. Available at: https://batteriesnews.com/solid-state-nasa-battery-beats-model-y-4680-pack-energy-density-stacking-cells-one-case/. (Accessed: Feb. 12, 2024).
[525] Sagoff, J. 2023. Scientists Develop More Humane, Environmentally Friendly Battery Material. Argonne National Laboratory. Last revised: Jan. 30, 2023. Available at: https://www.anl.gov/article/scientists-develop-more-humane-environmentally-friendly-battery-material. (Accessed: Feb. 12, 2024).
[526] Visnic, B. 2023. SAE International. Battery Show opens as automakers, suppliers intensify EV battery investments. Available at: https://www.sae.org/news/2023/09/2023-battery-show-opener. (Accessed: Apr. 1, 2024).

on available data, [527,528] NMC622 is more representative for our model year 2022 base year battery costs than LFP, and any additional cost reductions from manufacturers switching to LFP chemistry-based battery packs (or high-nickel cathode chemistries, for that matter) in years beyond 2022 are accounted for through learning. As a reminder, in this analysis, we account for the potential cost savings for *future* battery cell chemistries using a learning rate applied to the battery pack DMC. As discussed above, the battery chemistry we use is intended to reasonably represent what is used in U.S. battery manufacturing in model year 2022, the DMC base year (in 2021$) for our BatPaC calculations.

3.3.5.1.2. Battery Plant Production Volume

In practice, a single battery plant can produce packs using different cell chemistries with different power and energy specifications, as well as varying battery pack construction designs with different cell interconnectivities (to alter overall pack power end energy specifications) and thermal management strategies for the same base chemistry. However, in BatPaC, a battery plant is assumed to manufacture and assemble a specific battery pack design, and all cost estimates are based on one single battery plant manufacturing only that specific battery pack. For example, if a manufacturer has more than one EV and each uses a specific battery pack design, a BatPaC user would include manufacturing volume assumptions for each design separately to represent each plant producing each specific battery pack. As a consequence, we examine battery pack designs for vehicles sold in model year 2022 to determine a reasonable manufacturing plant production volume assumption. We consider each assembly line and material processing designed for a specific battery pack and for a specific BEV as an individual battery plant. Since battery technologies are still evolving, it is likely to be some time before battery cells can be treated as commodity where the specific numbers of cells are used for varying battery pack applications and all other metrics remain the same. Table 3-77 shows the assumed base year (model year 2022) battery manufacturing plant production volume for this analysis.

Table 3-77: Battery Manufacturing Plant Production Volume Assumption for Different Electrification Technologies for MY 2022

Technology	Production Volume
Mild HEV	200,000
Strong HEV	200,000
PHEVs	20,000
BEVs	60,000

Similar to previous rulemakings, we used BEV sales as a starting point to analyze potential base modeled battery manufacturing plant production volume assumptions. Since actual production data for specific battery manufacturing plants are extremely hard to obtain, and the battery cell manufacturer is not always the battery pack manufacturer,529 we calculated an average production volume per manufacturer metric to approximate BEV production volumes for this analysis. This metric was calculated by taking an average of all pre-model year (PMY) manufacturer's battery energy across all BEVs reported in vehicle manufacturer's pre-model year 2022 reports530 and was divided by the averaged sales-weighted energy per-vehicle; the resulting volume was then rounded to the nearest 5,000. This process was repeated for all other electrified vehicle technologies, as reflected in Table 3-77 above. Despite the absence of direct production data, we were able to correlate the known, accurate, and related PMY data from manufacturers – such as vehicle model and sales metrics – to give a high level of confidence in the base year plant production volume estimates.[531] An example calculation below, in Table 3-78, **Error! Reference source not found.**, and **Error! Reference**

[527] Rho Motion. 2023. EV & Battery monthly & quarterly subscriptions. (Proprietary data).
[528] International Energy Agency. Global EV Outlook 2023 (April 2023). Available at https://www.iea.org/reports/global-ev-outlook-2023. (Accessed: Feb. 12, 2024).
[529] Zhou, Y. et al. 2021. Lithium-Ion Battery Supply Chain for E-Drive Vehicles in the United States: 2010-2020. ANL/ESD-21/3. Argonne National Laboratory: Argonne, Ill. Available at: https://publications.anl.gov/anlpubs/2021/04/167369.pdf. (Accessed: Feb. 12, 2024).
[530] 49 CFR 537.7 - Pre-model year and mid-model year reports.
[531] NHTSA used publicly available range and pack size information and linked the information to vehicle models.

source not found. outline how the sales-weighted energy per vehicle production volume estimates are calculated with Table 3-14 showing several (theoretical) example BEV models, their production volumes, and pack energy that are representative of industry today.

Table 3-78: Example BEV Model Battery Packs

Electrification Level	Vehicle Make	Vehicle Model	Production Volume	Battery Pack Energy
BEV	Make A	Model A1	70,000	80kWh
BEV	Make A	Model A2	3,000	100kWh
BEV	Make B	Model B1	4,000	90kWh
BEV	Make C	Model C1	18,000	70kWh

The average energy (E_{avg}) across all BEVs in the fleet is initially found. In this example, the average energy is calculated as the sum of the pack energy divided by the number of vehicle models:

Equation 3-2: Example Average BEV Energy Calculation

$$E_{avg} = \frac{E_{Model\ A1} + E_{Model\ A2} + E_{Model\ B1} + E_{Model\ C1}}{N_{Vehicle\ models}} = \frac{80kWh + 100kWh + 90kWh + 70kWh}{4} = 85kWh\ average\ energy\ (theoretical\ example)$$

Next, the average production volume (P_{avg}) for this example was found via the sales weighted energy per vehicle by taking the product of a model's pack energy ($E_{Model\ xn}$) and production volume ($P_{Model\ xn}$) across all example vehicle models – with the sum of all models then divided by the average pack energy (E_{avg}), found from the previous equation:

Equation 3-3: Example Sales-Weighted Average Production Volume

$$P_{avg} = \frac{(E_{Model\ A1} * P_{Model\ A1}) + (E_{Model\ A2} * P_{Model\ A2}) + (E_{Model\ B1} * P_{Model\ B1}) + (E_{Model\ C1} * P_{Model\ C1})}{E_{avg}}$$
$$= \frac{(80kWh * 70{,}000) + (100kWh * 3{,}000) + (90kWh * 4{,}000) + (70kWh * 18{,}000)}{85kWh} = 104{,}235.3$$
$$\approx 105{,}000\ average\ BEV\ production\ (THEORETICAL\ EXAMPLE\ ONLY)$$

Once the average BEV production (P_{avg}) was found, it was rounded to the nearest 5,000; for this theoretical example, the production volume is rounded up from 104,235.3 to 105,000 vehicles. This process was used to determine production volumes for each of the electrified powertrain technologies in the fleet. Our final battery manufacturing plant production volume assumptions for different electrification technologies are as follows: mild hybrid and strong hybrids are manufactured assuming 200,000 packs, PHEVs are manufactured assuming 20,000 packs, and BEVs are manufactured assuming 60,000 packs.

We observed battery pack designs for BEVs sold both in the U.S. and globally; manufacturers design BEVs to suit local or regional duty cycles due to local geography and climate, customer preferences, affordability, supply constraints, and local laws. As a consequence, BEVs sold in the United States commonly have different performance metrics and battery technology compared to the same BEV sold in other parts of the world.[532] Accordingly, for this analysis, we considered U.S. sales – not global sales – when estimating battery pack production volume. We believe it was reasonable to consider U.S. sales for purposes of this calculation, rather than global sales, based on the best available data we had at the time of modeling and based on our understanding of how manufacturers design BEVs for particular markets.[533] However, manufacturers may take advantage of design overlap across markets to maintain cost reduction progress in battery technology. A manufacturer may have previously sold the same vehicle with different battery packs in two different markets, but as the outlook for battery materials and global economic events dynamically shift, manufacturers could take advantage of significant design overlap and other synergies such as vertical integration to introduce lower-cost battery packs in markets that were previously perceived to have different design requirements.[534] To the extent that manufacturers' costs are based more closely on global volumes of battery packs produced, our base year battery pack production volume assumption could potentially be conservative; however, as discussed further below, our base year model year 2022 battery pack costs fall well within the range of reasonable estimates based on 2023 data.

3.3.5.1.3. Battery Pack Direct Manufacturing Costs

Table 3-79 and Table 3-80 show BEV3 battery pack costs for all vehicle technology classes. These tables demonstrate how the cost per kW / kWh varies with the size of the battery pack. While the overall cost of a battery pack will increase for higher power /energy battery packs, the cost per kW / kWh decreases. This represents the cost of hardware that is needed in all battery packs but is deferred across more kW / kWh in larger packs, thus reducing the per kW / kWh cost.

The full range of BatPaC-generated battery direct manufacturing costs are located in ANL - Summary of Main Component Performance Assumptions_NPRM_2206. Note that these charts represent the direct manufacturing cost using a dollar per kW / kWh metric; battery absolute costs used in the analysis by technology key can be found in the CAFE Model Battery Costs File.

Table 3-79: $/kWh Battery Packs Costs – Compact Through Midsize BEV3

$/kWh at Pack Level (Total Energy) for Compact Through Midsize Vehicle Technology Class						
BEV3		Energy, kWh				
		30.0	50.0	70.0	90.0	120.0
Power, kW	20.0	$174	$145	$133	$125	$119
	40.0	$174	$146	$133	$125	$119
	60.0	$175	$146	$133	$126	$119
	80.0	$175	$146	$133	$126	$120
	100.0	$176	$147	$134	$126	$120
	120.0	$177	$147	$134	$126	$120

[532] Rho Motion. 2023. EV Battery monthly assessment. Figure: YTD weighted average BEV, PHEV and combined pack size by region, PC & light-duty vehicle. (Proprietary data).
[533] As an example, a manufacturer might design a BEV to suit local or regional duty cycles (i.e., how the vehicle is driven day-to-day) due to local geography and climate, customer preferences, affordability, supply constraints, and local laws. This is one factor that goes into chemistry selection, as different battery chemistries affect a vehicle's range capability, rate of degradation, and overall vehicle mass.
[534] As an example, some U.S. Tesla Model 3 and Model Y battery packs use a nickel cobalt aluminum (Lithium Nickel Manganese Cobalt Aluminum Oxide cathode with Graphite anode, commonly abbreviated as NCA)-based cell, while the same vehicles for sale in China use LFP-based packs. However, Tesla has introduced LFP-based battery packs to some Model 3 vehicles sold in the U.S., showing how manufacturers can take advantage of experience in other markets to introduce different battery technology in the United States. See Electric Vehicle Database. Tesla Model 3 Standard Range Plus LFP. Available at: https://ev-database.uk/car/1320/Tesla-Model-3-Standard-Range-Plus-LFP. (Accessed: Feb. 12, 2024). See the Tesla Model 3 Owner's Manual for additional considerations regarding LFP-based batteries. Available at: https://www.tesla.com/ownersmanual/model3/en_jo/GUID-7FE78D73-0A17-47C4-B21B-54F641FFAEF4.html. (Accessed: Feb. 12, 2024).

	140.0	$177	$147	$134	$126	$120
	160.0	$178	$148	$134	$127	$120
	180.0	$178	$148	$135	$127	$120
	200.0	$179	$148	$135	$127	$120
	240.0	$180	$149	$135	$127	$121
	280.0	$183	$150	$136	$128	$121
	320.0	$189	$151	$136	$128	$121
	400.0	$200	$152	$137	$129	$122

Table 3-80: $/kWh Battery Packs Costs – SUV Through Pickup (Light-Duty & HDPUV) BEV3

$/kWh at Pack Level (Total Energy) for SUV Through Pickup (LD & HDPUV) Vehicle Technology Class													
BEV3		Energy, kWh											
		30.0	50.0	70.0	90.0	120.0	140.0	160.0	180.0	200.0	250.0	300.0	350.0
Power, kW	20.0	$182	$151	$137	$129	$121	$118	$116	$114	$113	$110	$108	$106
	40.0	$183	$151	$137	$129	$121	$118	$116	$114	$113	$110	$108	$106
	60.0	$183	$151	$137	$129	$122	$118	$116	$114	$113	$110	$108	$106
	80.0	$184	$152	$137	$129	$122	$118	$116	$115	$113	$110	$108	$106
	100.0	$184	$152	$138	$129	$122	$119	$116	$115	$113	$110	$108	$106
	120.0	$185	$152	$138	$130	$122	$119	$117	$115	$113	$110	$108	$106
	140.0	$185	$153	$138	$130	$122	$119	$117	$115	$113	$110	$108	$106
	160.0	$186	$153	$138	$130	$122	$119	$117	$115	$113	$110	$108	$106
	180.0	$187	$154	$139	$130	$122	$119	$117	$115	$113	$110	$108	$107
	200.0	$187	$154	$139	$130	$123	$119	$117	$115	$113	$110	$108	$107
	240.0	$188	$155	$139	$131	$123	$119	$117	$115	$114	$110	$108	$107
	280.0	$191	$155	$140	$131	$123	$120	$117	$116	$114	$111	$108	$107
	320.0	$197	$156	$140	$131	$123	$120	$118	$116	$114	$111	$108	$107
	400.0	$208	$157	$141	$132	$124	$120	$118	$116	$114	$111	$109	$107

3.3.5.2. Non-Battery Electrification Component Costs

Batteries and relative battery components are the biggest cost driver of electrification; however, non-battery electrification components, such as electric motors, power electronics, and wiring harnesses, also add to the total cost required to electrify a vehicle. Different electrified vehicles have variants of non-battery electrification components and configurations to accommodate different vehicle classes and applications with respective designs; for instance, some BEVs may be engineered with only one electric motor and some BEVs may be engineered with two or even four electric motors within their powertrain to provide all wheel drive function. In addition, some electrified vehicle types still include conventional components, like an ICE and traditional transmission. Chapter 3.3.5.3 discusses how the battery costs, non-battery electrification component costs, and other CONV technology costs come together to create a total vehicle cost for various levels of electrified vehicles.

For all other electrified vehicle powertrain types, we group non-battery electrification components into four major categories: electric motors/generators, power electronics (generally including the DC/DC converter, inverter, and power distribution module), charging components (charger, charging cable, and high voltage cables), and thermal management system(s).

We further group the components into those comprising the electric traction drive system (ETDS), and all other components. Although each manufacturer's ETDS and power electronics vary between the same electrified vehicle types and between different electrified vehicle types, we consider the ETDS for this analysis to be comprised of the electric motor and inverter, power electronics, and thermal management system. Table 3-81 shows our assignments for each of the non-battery electrification components to HEVs, PHEVs, BEVs, and FCEVs in the analysis.

Table 3-81: Non-Battery Electrification Component and Vehicle Assignment for Both LD and HDPUV

Major Non-Battery Electrification Components	HEV	PHEV	BEV	FCEV
Electric Motor	X	X	X	X
*Electric Generator	X	X		
Power Electronics	X	X	X	X
DC/DC Converter	X	X	X	X
Charging Port & High Voltage cable	N/A	X	X	N/A
On-board Charger	N/A	X	X	N/A
Thermal Management System	X	X	X	X
Fuel Cell Stack	N/A	N/A	N/A	X
*Electric generators listed here typically only apply to HEVs and PHEVs with power-split architectures, in which the generator is connected to the ICE to recharge the high-voltage battery.				

When researching costs for different non-battery electrification components, we found that different reports vary in components considered and cost breakdown. This is not surprising, as vehicle manufacturers use different non-battery electrification components in different vehicles systems, or even in the same vehicle type, depending on the application.[535,536] As detailed below, we apply costs for the major non-battery electrification components on a dollar per kilowatt ($/kW) basis to align with the normalized costs for a system's peak power rating as presented in U.S. DRIVE's Electrical and Electronics Technical Team (EETT) Roadmap report[537] – one of the sources we use for non-battery electrification component costs. This approach captures components in most, but not all, manufacturers' systems; however, we believe that this is a reasonable metric and approach for this analysis, given the non-standardization of electrified powertrain designs and subsequent component specifications.

As discussed in Chapter 2.4, we adjust costs in the Technologies Input File to account for three variables: retail price equivalence (or RPE, which is 1.5 times the DMC), the technology learning curve, and the adjustment of the dollar value to 2021$ for this analysis. While HDPUVs have larger non-battery electrification componentry than light-duty vehicles, the cost calculation methodology is identical, in that the

[535] For example, the model year 2020 Nissan Leaf does not have an active cooling system whereas Chevy Bolt uses an active cooling system.
[536] Argonne 2022. AMTL D3. Electric Vehicle Testing. Available at: https://www.anl.gov/es/electric-vehicle-testing. (Accessed Feb. 12, 2024).
[537] DOE. 2017. Electrical and Electronics Technical Team Roadmap. Driving Research and Innovation for Vehicle Efficiency and Energy Sustainability. Available at: https://www.energy.gov/eere/vehicles/articles/us-drive-electrical-and-electronics-technical-team-roadmap. (Accessed: Feb. 12, 2024).

$/kW metric is the same, but the absolute costs are higher. As a result, HDPUVs and light-duty vehicles share the same non-battery electrification DMCs.

3.3.5.2.1. Micro Hybrid and Mild Hybrid Costs

Beginning with the least complex electrification systems, the SS12V micro hybrid system cost in this analysis is based on a single small motor and battery; the motor is a fixed cost regardless of the engine type the system is paired with (e.g., turbocharged or naturally aspirated), but the cost varies by vehicle class. We use motor costs from the 2016 Draft TAR and update the cost to 2021$.[538] The DMC for the SS12V motor is $171.55 for the small car, medium car, and small SUV vehicle classes and $229.11 for the medium SUV, light-duty pickup, and all HDPUV vehicle classes.

Similar to the SS12V system, the 48V BISG mild hybrid non-battery electrification component costs are fixed for all technology classes. We used the A2Mac1 database to develop a bill of materials for the BISG system, and cost the components using two sources, as explained further below. Table 3-82 lists the non-battery electrification components that comprise the mild hybrid system, and the cost of those components in the analysis.

Table 3-82: Cost Estimate of BISG Components in 2021$

Components	DMC	RPE
Motor, inverter, & cooling system (10kW)	$197.92	$296.88
DC/DC converter (2kW)	$197.92	$296.88
Water pump	$46.25	$69.38
Wiring harness	$31.19	$46.79
Connecters	$10.76	$16.14
Belt pulley modifications to AC compressor	$10.76	$16.14
Auxiliary electric oil pump to transmission	$49.48	$74.22
Modifications to auxiliary brake pump	$46.25	$69.38
Brackets for motor and battery attachment	$16.13	$24.20
Total non-battery component cost	$606.66	$910.01

We use a dollar per kilowatt metric derived from the 2017 EETT Roadmap report, discussed in more detail below, for the electric motor, inverter, cooling system, and DC/DC converter costs.[539] For all other BISG component costs shown in Table 3-82, we rely on an EPA-sponsored FEV teardown of a 2013 Chevrolet Malibu ECO with eAssist.[540] FEV estimates the direct manufacturing cost of the BISG system (without batteries) to be $1,045 in 2013 dollars, which is equivalent to $1,218.71 in 2021 dollars — this includes a cost adjustment for reduced voltage insulation. Even though the 2013 Chevrolet Malibu considered in the study used a 115V system, we determined that structural components, like the motor and battery attachment brackets, would translate fairly across BISG systems, regardless of system voltage.

[538] Draft TAR, at 5–453.
[539] DOE. 2017. Electrical and Electronics Technical Team Roadmap. Driving Research and Innovation for Vehicle Efficiency and Energy Sustainability. Available at: https://www.energy.gov/eere/vehicles/articles/us-drive-electrical-and-electronics-technical-team-roadmap. (Accessed: Feb. 12, 2024).
[540] FEV. 2014. Light Duty Vehicle Technology Cost Analysis 2013 Chevrolet Malibu ECO with eAssist BAS Technology Study. FEV P311264. Contract no. EP-C-12-014, WA 1-9.

To validate these costs, we considered the 2019 Dodge Ram eTorque system retail price. Using the publicly available retail price,[541] we estimated the normalized cost of the system at $1,195 for the water-cooled system and $1,450 for the air-cooled system in 2018 dollars after the removal of an estimated RPE and learning factor. In addition, the 2015 NAS report estimates the cost range of BISG technology at $888 to $1,164 in 2010 dollars in 2025.[542] This is equivalent to a range of $1,095.75 to $1,436.33 in 2021 dollars in 2025. Broadly, our total BISG system cost, including the battery, conservatively matches these estimates.

3.3.5.2.2. Strong Hybrid, Plug-in Hybrid, and Battery Electric Vehicle Costs

As discussed above, to estimate the cost of the ETDS, we used U.S. DRIVE's EETT Roadmap report. The EETT Roadmap report reflects considerable work by the Department of Energy's Vehicle Technology Office collaboratively with U.S. DRIVE, a government-industry partnership. The EETT Roadmap report estimates the 2017 manufacturing cost of a commercial on-road 100 kW ETDS consisting of a single electric traction motor and inverter; the reported costs are approximately $1,800, with the cost of the electric motor accounting for $800, and approximately $1,000 for the inverter, equaling $18.00/kW for the ETDS. This is the equivalent to $19.80/kW in 2021$. We compared these costs with the UBS model year 2016 Chevy Bolt teardown;[543] the reported cost of the electrical components in the ETDS summed to $2,619 for a 150 kW (2016 Chevy Bolt nominal power) ETDS. Normalizing this cost resulted in $19.59/kW in 2021$, which is in agreement with the cost calculated from U.S. DRIVE's EETT Roadmap report.[544]

The EETT Roadmap report did not explicitly estimate the cost of other electrical equipment present in electrified powertrains, such as on-board chargers, DC/DC converters, high voltage cables, and charging cables. We relied on the UBS model year 2016 Chevy Bolt teardown report to estimate those individual costs for some categories of strong hybrid components, and all other PHEV and BEV components.

The strong hybrid high-voltage cable costs are from the EPA-sponsored 2011 Ford Fusion HEV teardown study.[545] We adjusted the costs for high voltage cables from the 2011 Ford Fusion HEV teardown study to 2021$ and apply that to both PS and P2 strong hybrid cables.

Table 3-83 shows our cost estimates for the ETDS from the EETT Roadmap report, the UBS model year 2016 Chevy Bolt teardown report, and the EPA-sponsored FEV report (with updated 2021$ costs).

Table 3-83: Cost Estimates from the EETT Roadmap Report, UBS MY 2016 Chevy Bolt Teardown, and FEV 2011 Ford Fusion HEV Teardown

Non-Battery Electrical Components	EETT Roadmap Report (2017$ in DMC Year 2017)	UBS MY 2016 Chevy Bolt Teardown (2017$ in DMC Year 2017)	Assumptions	EPA-Sponsored FEV Report (Updated 2021$ for Analysis)
ETDS	$18/kW	$17.76/kW	Based on e-motor peak power	$19.80/kW
On-Board Charger	no information provided	$85/kW	Based on vehicle requirement (7 kW for BEVs, 2 kW for PHEVs)	$93.54/kW
DC/DC Converter	no information provided	$90/kW	Based on converter rated power (2 kW)	$100.94/kW

541 Colwell, K.C. 2019. The 2019 Ram 1500 eTorque Brings Some Hybrid Tech, If Little Performance Gain, to Pickups. Car and Driver. Last revised: Mar. 14, 2019. Available at: https://www.caranddriver.com/reviews/a22815325/2019-ram-1500-etorque-hybrid-pickup-drive. (Accessed: Feb. 12, 2024).
542 2015 NAS report, at 305.
543 Hummel, P. et al. 2017. UBS Evidence Lab Electric Car Teardown – Disruption Ahead?. UBS. Available at: https://neo.ubs.com/shared/d1ZTxnvF2k. (Accessed: Feb. 12, 2024).
544 We normalize the cost of the ETDS for the 2016 Chevy Bolt by summing the ETDS components costs and dividing by e-motor power rating (150 kW).
545 EPA. 2011. Light Duty Technology Cost Analysis, Power-Split and P2 HEV Case Studies. Technical Report. EPA-420-R-11-015. Assessment and Standards division. Prepared for EPA by FEV, Inc. Available at: https://nepis.epa.gov/Exe/ZyPDF.cgi/P100EG1R.PDF?Dockey=P100EG1R.PDF. (Accessed: Feb. 12, 2024).

High Voltage Cables and Charging Cords for BEVs and PHEVs	no information provided	$450	Fixed cost rated for 360V	$495.21
High Voltage Cables for Strong Hybrids	no information provided	no information provided	Fixed cost	$100.44

3.3.5.3. Battery and Non-Battery Learning Curves

3.3.5.3.1. Battery Learning Curves

To reflect the evolution of battery manufacturing and for better alignment of battery assumptions between government agencies, the Department of Energy and Argonne National Laboratory developed battery cost correlation equations from BatPaC for use in both the NHTSA CAFE and EPA GHG analyses.[546] These cost equations – developed for use through model year 2035 – were tailored for different vehicle segments,[547] different levels of electrification,[548] and anticipated plant production volumes.[549] These equations represent cost improvements achieved from advanced manufacturing, pack design, and cell design with current and anticipated future battery chemistries,[550] design parameters, forecasted market prices, and vehicle technology penetration.

The battery cost correlation Equation 3-4[551,552] below uses different coefficients (see Table 3-84) for HEVs[553] compared to the coefficients used for PHEVs and BEVs; note that for PHEVs and BEVs, the coefficients differ for Ni/Mn (NMC) and LFP cathode chemistries.

Equation 3-4: Battery Pack Cost Correlation Equation

$$C_{pack}=A+\frac{B}{x^C}-D(y-2023)e^{E(y-2023)}$$

Table 3-84: Correlation Equation Coefficients

	HEV (≤ 5kWh)	BEV/PHEV	
Coefficient	**Ni/Mn**	**Ni/Mn**	**LFP**
A	122.9	128.9	120.6
B	509.6	1480	1535
C	0.7649	1.164	1.148
D	4.443	5.278	10.04
E	0.01018	-0.01290	-0.08346

546 ANL. 2024. Cost Analysis and Projections for U.S.-Manufactured Automotive Lithium-ion Batteries. ANL/CSE-24/1. Available at: https://publications.anl.gov/anlpubs/2024/01/187177.pdf. (Accessed: Mar. 12, 2024).
547 The vehicle classes considered in this project include compact cars, midsize cars, midsize SUVs, and pickup trucks.
548 The levels of electrification considered in this project include light-duty HEVs, PHEVs, and BEVs (~250 and ~300 mile ranges) as well as medium/heavy-duty BEVs.
549 Production volumes were determined for each vehicle class and type for each model year. See, DOE. Argonne National Laboratory. Cost Analysis and Projections for U.S.-Manufactured Automotive Lithium-ion Batteries. ANL/CSE-24/1. Equation 1 and Table 13. Available at: https://www.osti.gov/biblio/2280913/. (Accessed: Jan. 25, 2024).
550 Battery cathode chemistries considered in this project include nickel-based materials (NMC622, NMC811, NMC95, and LMNO) as well as lower-cost LFP cathodes; varying percentages of silicon content (5%, 15%, and 35%) within a graphite anode were considered, as well.
551 C_{pack} unit of measurement is in $/kWh.
552 The coefficients used assume a $50/hour labor rate.
553 ≤ 5kWh battery, Ni/Mn cathode. This equation was also used for FCEV batteries whose battery packs typically have battery energy below 5kWh.

The remaining correlation equation variables *x* and *y* correspond to pack energy (kWh) and model year, respectively – inputs ultimately used to develop learning curves for each vehicle class and level of electrification technology for our analysis.

Autonomie full vehicle model simulation data[554] was used to determine average battery pack energy across vehicle segments (variable *x*). See Table 3-85 below for the corresponding average pack energy values used as inputs to the battery cost correlation equations.

[554] For details of how Autonomie Full Vehicle Model simulations was used for this rulemaking see Chapter 2.4.

Table 3-85: Average Battery Pack Energy Values from Autonomie Full Vehicle Model Simulations Across Vehicle Segments and Electrification Technologies

Average Pack Energy (kWh)	SmallCar	SmallCar Perf	MedCar	MedCarP erf	SmallSUV	SmallSUV Perf	MedSUV	MedSUVP erf	Pickup	PickupHT
BISG	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
P2D	0.90	0.94	1.03	1.10	1.03	1.12	1.12	1.22	1.12	1.22
P2SGDID	0.90	0.94	1.03	1.10	1.03	1.12	1.12	1.22	1.12	1.22
P2S	0.90	0.94	1.03	1.10	1.03	1.12	1.12	1.22	1.12	1.22
P2SGDIS	0.92	0.95	1.04	1.12	1.04	1.13	1.13	1.26	1.13	1.26
P2TRB0	0.92	0.94	1.04	1.12	1.04	1.13	1.13	1.26	1.13	1.26
P2TRBE	0.92	0.94	1.04	1.12	1.04	1.13	1.13	1.26	1.13	1.26
P2TRB1	0.92	0.95	1.04	1.12	1.04	1.13	1.13	1.26	1.13	1.26
P2TRB2	0.92	0.95	1.04	1.12	1.04	1.13	1.13	1.26	1.13	1.26
P2HCR	0.92	0.95	1.04	1.12	1.04	1.13	1.13	1.26	1.13	1.26
P2HCRE	0.92	0.95	1.04	1.12	1.04	1.13	1.13	1.26	1.13	1.26
SHEVPS	1.21	2.16	1.71	3.35	1.51	2.21	1.53	2.43	1.53	2.43
PHEV20T	8.89	9.33	9.51	10.01	10.80	11.36	11.69	12.62	11.69	12.62
PHEV50T	22.41	23.55	24.08	25.39	27.21	28.58	29.44	31.70	29.44	31.70
PHEV20H	8.83	9.23	9.44	9.89	10.70	11.21	11.57	12.45	11.57	12.45
PHEV50H	22.27	23.33	23.92	25.09	26.93	28.18	29.14	31.25	29.14	31.25
PHEV20PS	8.37	8.76	9.05	9.59	10.30	10.76	11.28	12.08	11.28	12.08
PHEV50PS	19.23	20.34	20.74	22.11	23.71	25.04	25.92	28.10	25.92	28.10
BEV1	48.81	51.18	52.66	55.08	60.79	63.28	66.23	70.92	66.23	70.92
BEV2	62.25	65.28	67.16	70.28	77.50	80.70	84.41	90.39	84.41	90.39
BEV3	77.28	81.07	83.37	87.18	96.31	100.30	104.79	112.18	104.79	112.18
BEV4	116.62	122.40	125.95	131.78	145.61	151.69	158.04	169.30	158.04	169.30
FCEV	0.95	1.04	1.13	1.22	1.16	1.25	1.24	1.43	1.24	1.43

Additionally, due to the increasing prevalence of LFP displacing NMC cathodes in the U.S. EV market, NHTSA uses a dynamic NMC/LFP mix between the battery cost correlation equations, referred to as a composite correlation equation; LFP market projections[555] used for the mix are noted below in Table 3-86. For the model years that the composite cost equation covers (for model years through 2035), NMC battery cathode chemistry is assumed for the remaining market share. Note the composite cost equation only corresponds with BEV and PHEV electrification technologies and not HEV or FCEV electrification technologies.

Table 3-86: U.S. Market Share Cathode Projections for BEVs and PHEVs

Model Year	Percent LFP Cathode Market Share (U.S.)	Remaining NMC Market Share (U.S.)
2021	1%	99%
2022	3%	97%
2023	8%	92%
2024	10%	90%
2025	16%	84%
2026	17%	83%
2027	18%	82%
2028	19%	81%
2029	19%	81%
2030	19%	81%
2031	19%	81%
2032	19%	81%
2033	19%	81%
2034	19%	81%
2035	19%	81%

The subsequent battery cost correlations are unique for each vehicle type, across electrification technologies through model year 2035. For this analysis, a learning plateau cost constant is used in place of the battery cost correlations between model years 2022 and 2025 to reflect the combination of increasing mineral costs,

555 A composite learning curve (used for PHEV and BEV battery cost projections) was developed, in coordination with DOE/ANL and EPA, to include a North American market mix of NMC and LFP chemistries (dynamic, over time); the NMC/LFP market presence projections values were based on (averaged, rounded, and smoothed) Rho Motion and Benchmark Mineral Intelligence proprietary data.

changing demand, and uncertainty in manufacturers ability to increase production in such short time frame.[556,557,558]

Beyond the extent of the battery cost correlation equation, starting in model year 2036, a constant 1.5 percent learning rate[559] was used through model year 2050. A 1.5 percent year-over-year cost reduction results in a gradual rate of reduction and projected costs in 2050 that are consistent with or conservative with respect to the literature. For example, Figure 9 of Mauler et al. (2021)[560] shows that a comprehensive compilation of battery cost projections in the literature predict a 2.5 to 3 percent annual cost reduction between 2035 and 2050 resulting in a cost of about $71/kWh in 2050. Applied to the 2035 cost from the ANL correlations, a 1.5 percent rate results in a similar trend.

In combination with our base year (model year 2022) DMC battery costs (found in the CAFE Model Battery Costs File – also unique across vehicle types and across electrification technologies) and a retail price equivalence (RPE) factor, the resulting battery learning curves were then calculated and embedded in the Technologies Input File for use in our analysis. For more information on our base year battery pack direct manufacturing costs, see Chapter 3.3.5.1.3. For more information on the Technologies Input File, see Chapter 2.1.3 and Chapter 2.1.9.

The agencies determined this battery learning approach was a reasonable method for representing manufacturing technologies that are rapidly advancing. However, a level of uncertainty is assumed and is characterized with several additional sensitivity analyses;[561] results of battery cost sensitivity cases can be found in FRIA Chapter 9.2.2.3.

Table 3-87 below shows a comparison of battery cost estimates from this analysis and other sources. Note that the costs presented in this table represent the cost to manufactures at the battery pack level, i.e., the direct manufacturing cost. The sources used to create this table did not uniformly distinguish a DMC source year, so some values vary slightly based on inflation.

Table 3-87: Battery Pack Cost Estimates from Other Years and Sources ($/kWh)

	2022-2024[562]	2025	2027	2030	2035
NHTSA MY 2027-2032 Final Rule (2021$)	$134[563]	$134	$106	$93	$75
NHTSA MY 2027-2032 NPRM (2021$)[564, 565]	$134	$134	$124	$112	$96

556 After model year 2025, the learning rate continues to trend downward — since the cost of lithium has increased since 2020, which is not expected to decline significantly until additional capacity (mining, materials processing, and cell production) comes on-line, although prices have fallen from 2022 highs at the time of writing. We believe that a continuation of high prices for a few years followed by a decrease to near previous levels is reasonable because world lithium resources are more than sufficient to supply a global EV market and higher prices should continue to induce investment in lithium mining and refining.

557 U.S. Geological Survey. 2023. Lithium Statistics and Information. Available at: https://www.usgs.gov/centers/national-minerals-information-center/lithium-statistics-and-information. (Accessed: Dec. 13, 2023).

558 Barlock, T.A. et al. February 2024. Securing Critical Materials for the U.S. Electric Vehicle Industry. ANL-24/06. Final Report. Available at: https://publications.anl.gov/anlpubs/2024/03/187907.pdf. (Accessed: Apr. 5, 2024).

559 EPA and NHTSA both use the 1.5% learning rate from MY 2036 onward for our respective light-duty final rules.

560 Mauler et al., "Battery cost forecasting: a review of methods and results with an outlook to 2050," Energy Environ. Sci, v.14, at 4712-4739 (2021).

561 Considering the range of uncertainty and the large contribution of critical mineral cost has to the overall vehicle cost, we ran numerous battery cost-related sensitivity cases to recognize possible outcomes.

562 Sources generally provided estimates between 2022 and 2024.

563 The $/kWh direct manufacturing cost (DMC) estimate presented here is for a midsize passenger car BEV3 vehicle with a ~70kWh battery pack.

564 The $/kWh direct manufacturing cost (DMC) estimate presented here is for a midsize passenger car BEV3 vehicle with a ~70kWh battery pack. The values represented in previous NPRM documentation were that of a small SUV BEV3 with the same energy capacity.

565 The NPRM battery cost learning curve was based on a Mauler et al. paper. See Mauler, L., F. Duffner, W. Zeier and J. Leker, 2021. Battery cost forecasting: a review of methods and results with an outlook to 2050. Energy and Environmental Science. 4712-4739. Available at: https://pubs.rsc.org/en/content/articlelanding/2021/ee/d1ee01530c. (Accessed: May 31, 2023). Many of these selected studies focus on common-place lithium-ion battery (LIB) cathode chemistries for BEVs – such as lithium nickel manganese cobalt oxide (NMC), lithium nickel cobalt aluminum oxide (NCA), and lithium iron phosphate (LFP); however, some studies investigate the future-use of battery technologies such as solid-state (SSB) and lithium-sulfur (LSB), while other studies examine battery applications that more broadly coincide with hybrid electric vehicles (HEVs), energy stationary storage (ESS), consumer electronics, and medical devices. Thirty of the forecasts were based on bottom-up battery models and sixteen used estimated learning curves.

ICCT (2022)[566]	$131	$105		$74	$63
BNEF EV Outlook (2022)[567, 568, 569]	$138[570]		$94		
Orangi & Strømman – Techno-Economic Model (2022)[571]		$115			
NAS Report (2021)[572]		$90-$115		$65-$80	
Toyota (2020)[573]				$108	
Penisa (2020)[574]	$115.14				
Massachusetts Institute of Technology (MIT) (2019)[575]		$146		$131[576]	
Hsieh (2019)[577]				$93 - $141	
Nykvist (2019)[578]				$119	
BCG (2018)[579]		$138		$117	
UBS (2017)[580]		$130			

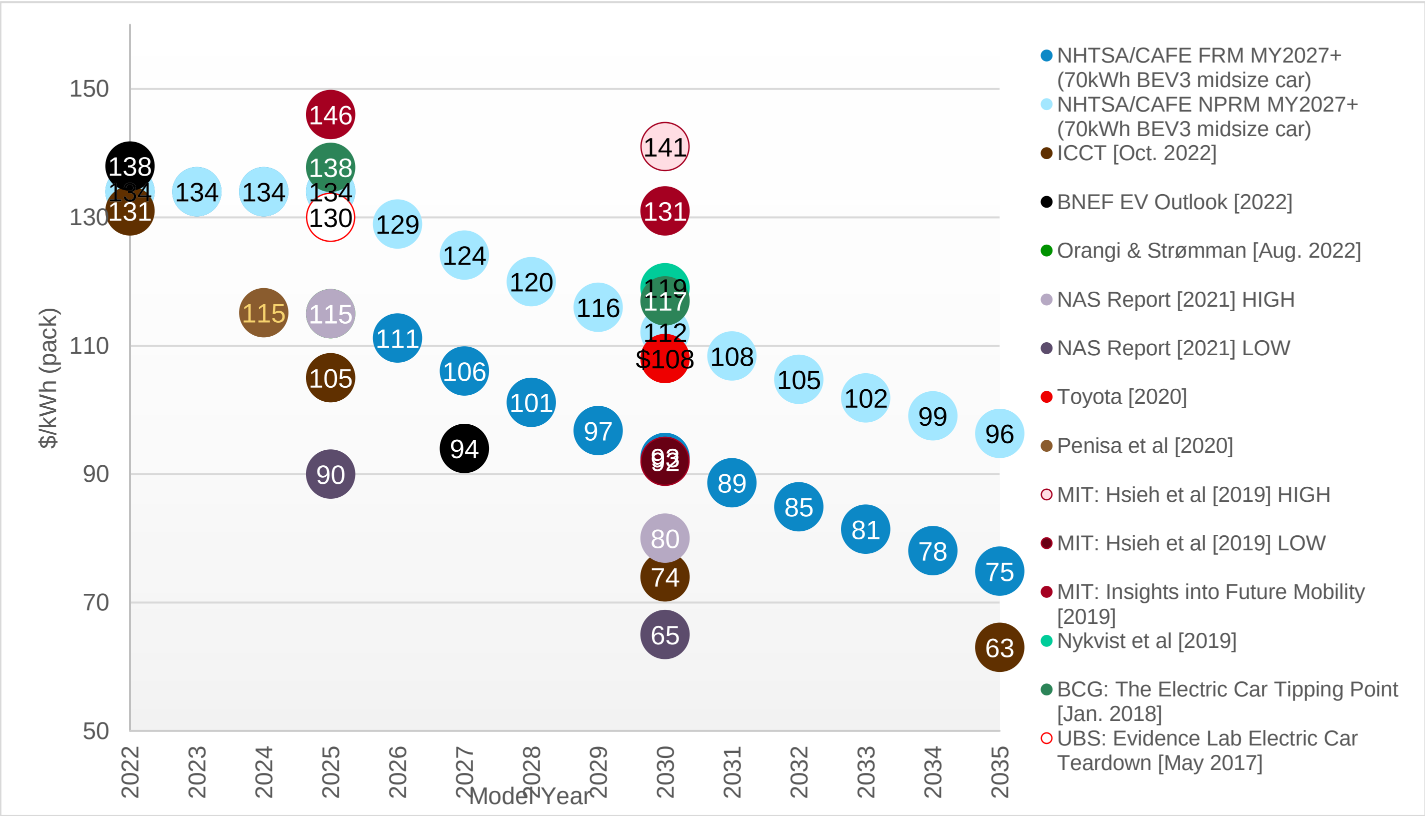
Each individual report uses a certain set of assumptions to arrive at a rate of cost reduction. Among all the different cost estimates, BNEF, the NAS report, and International Council on Clean Transportation (ICCT) predict the most optimistic year-over-year cost reductions. The NAS report assumes a battery learning rate of 5 percent per year but does not disclose the methodology for determining this assumed learning rate.[581] BNEF assumes that, despite recent cost hikes, battery pack costs will trend downwards – below $100/kWh by model year 2026 – as critical mineral extraction and refining efforts continue to ramp up.[582]

As shown in Figure 3-32, the learning rate we assume for model years through 2032 is more optimistic than the MIT report learning rate, and less optimistic than the 2021 NAS committee's learning rate. Using the same approach as the rest of our analysis – that our costs should represent an average achievable

[566] Slowik, P. et. al. 2022. Assessment of Light-Duty Electric Vehicle Costs and Consumer Benefits in the United States in the 2022-2035 Time Frame. International Council on Clean Transportation. Available at: https://theicct.org/wp-content/uploads/2022/10/ev-cost-benefits-2035-oct22.pdf. (Accessed: Feb. 12, 2024).
[567] BloombergNEF. 2022. Lithium-ion Battery Pack Prices Rise for First Time to an Average of $151/kWh. Last revised: Dec. 6, 2022. Available at: https://about.bnef.com/blog/lithium-ion-battery-pack-prices-rise-for-first-time-to-an-average-of-151-kwh/. (Accessed: Feb. 12, 2024).
[568] IEA. 2022. Global EV Outlook 2022 – Securing Supplies for an Electric Future. Executive Summary. International Energy Agency. at 1-221. Available at: https://iea.blob.core.windows.net/assets/ad8fb04c-4f75-42fc-973a-6e54c8a4449a/GlobalElectricVehicleOutlook2022.pdf. (Accessed: Feb. 12, 2024).
[569] BloombergNEF. 2023. Lithium-Ion Battery Pack Prices Hit Record Low of $139/kWh. Available at: https://about.bnef.com/blog/lithium-ion-battery-pack-prices-hit-record-low-of-139-kwh/. (Accessed: Feb. 12, 2024).
[570] BloombergNEF. 2022. The Race to Net Zero: The Pressures of the Battery Boom in Five Charts. Available at: https://about.bnef.com/blog/race-to-net-zero-the-pressures-of-the-battery-boom-in-five-charts/. (Accessed: Feb. 12, 2024).
[571] Orangi, S., Strømman, A.H. 2022. A Techno-Economic Model for Benchmarking the Production Cost of Lithium-Ion Battery Cells. *Batteries 2022.* Vol. 8(8): at 83. Available at: https://www.researchgate.net/publication/362537852_A_Techno-Economic_Model_for_Benchmarking_the_Production_Cost_of_Lithium-Ion_Battery_Cells. (Accessed: Feb. 12, 2024).
[572] 2021 NAS report, at 131. BEV300 medium car.
[573] Hamza, K. et al. 2020. On Modeling the Total Cost of Ownership of Electric and Plug-in Hybrid Vehicles. SAE Technical Paper 2020-01-1435. Available at: https://www.sae.org/publications/technical-papers/content/2020-01-1435/. (Accessed: Feb. 12, 2024).
[574] Penisa et al. 2020. Projecting the Price of Lithium-Ion NMC Battery Packs Using a Multifactor Learning Curve Model. *Energies 2020*. Vol. 13(20): at5276. Available at: https://www.mdpi.com/1996-1073/13/20/5276. (Accessed: Feb. 12, 2024).
[575] MIT Energy Initiative. 2019. Insights into Future Mobility. Cambridge, MA: MIT Energy Initiative. Available at http://energy.mit.edu/insightsintofuturemobility. (Accessed: Feb. 12, 2024).
[576] *Id*, at 78. MIT estimates $124/kWh in 2030 in 2019$. Converting $124/kWh results in $131.03/kWh in 2030 in 2021$.
[577] Hsieh, I.L et. al. 2019. Learning Only Buys You So Much: Practical Limits on Battery Price Reduction. *Applied Energy.* Volume Vol. 239: at 218-224. Available at: https://hdl.handle.net/1721.1/123880. (Accessed: Feb. 12, 2024).
[578] Nykvist, B. et al. 2019. Assessing The Progress Toward Lower Priced Long Range Battery Electric Vehicles. *Energy Policy, Elsevier*. Vol. 124(C):. at 144-55. Available at: https://www.sei.org/publications/assessing-progress-lower-priced-long-range-battery-electric-vehicles/. (Accessed: Feb. 12, 2024).
[579] Mosquet, X. et al. 2018. The Electric Car Tipping Point. Boston Consulting Group. Last revised: Jan. 11, 2018. Available at: https://www.bcg.com/publications/2018/electric-car-tipping-point.aspx. (Last Accessed: Feb. 12, 2024). This study provided cell cost estimates that the agencies converted to pack cost estimates using a multiplier of 1.3, as outlined in the Draft TAR at 5–124.
[580] Hummel, P. et al. 2017. UBS Evidence Lab Electric Car Teardown – Disruption Ahead?. UBS. Available at: https://neo.ubs.com/shared/d1ZTxnvF2k. (Accessed: Feb. 12, 2024).
[581] 2021 NAS report, at 4–67.
[582] BloombergNEF. 2022. Lithium-ion Battery Pack Prices Rise for First Time to an Average of $151/kWh. Last revised: Dec. 6, 2022. Available at: https://about.bnef.com/blog/lithium-ion-battery-pack-prices-rise-for-first-time-to-an-average-of-151-kwh/. (Accessed: Feb. 12, 2024).

performance across the industry – we believe that the battery DMCs with the learning curve applied provide a reasonable representation of potential costs across the industry. Figure 3-32 shows how the battery pack learning cost reduction compares to the other battery pack cost estimates from sources listed in Table 3-87, with our projected costs falling largely in the middle of the range of potential costs in future years.[583]

Figure 3-32: Comparing Battery Pack Cost Estimates from Multiple Sources



Additional discussion of battery learning rates is included in preamble Section III.D.3. As discussed above, there are inherent uncertainties in projecting future battery pack costs due to several factors. One way to bound the uncertainty in projecting battery pack costs is to perform a sensitivity analysis. We performed several related battery cost sensitivity analyses in relation to the reference baseline; these results are discussed in the FRIA.

3.3.5.3.2. Non-Battery Electrification Learning Curves

For the non-battery electrification component learning curves in both the light-duty and heavy-duty vans and pickups fleets, we used cost information from Argonne's 2016 Assessment of Vehicle Sizing, Energy Consumption, and Cost through Large-Scale Simulation of Advanced Vehicle Technologies report.[584] The report provides estimated cost projections from the 2010 lab year to the 2045 lab year for individual vehicle components.[585,586] We considered the component costs used in electrified vehicles and determined the learning curve by evaluating the year over year cost change for those components. Additionally, Argonne published a 2020 and a 2022 version of the same report; however, those versions did not include a discussion

[583] NPRM and FRM learning curve values are shown for a midsize passenger car BEV3 with a ~70kWh battery pack.
[584] Moawad, A. et al. 2016. Assessment of Vehicle Sizing, Energy Consumption and Cost Through Large Scale Simulation of Advanced Vehicle Technologies. ANL/ESD-15/28. Available at: https://publications.anl.gov/anlpubs/2016/04/126422.pdf. (Accessed: Feb. 12, 2024).
[585] ANL/ESD-15/28 at 116.
[586] DOE's lab year equates to five years after a model year, e.g., DOE's 2010 lab year equates to model year 2015.

of the high- and low-cost estimates for the same components.[587,588] Our learning estimates – generated using the 2016 report – align in the middle of these two ranges, and therefore we continue to apply the learning curve estimates based on the 2016 report. There are many sources that we could have picked to develop learning curves for non-battery electrification component costs; however, given the uncertainty surrounding extrapolating costs out to model year 2050, we believe these learning curves provide a reasonable estimate.

Table 3-88 and Table 3-89 show the learning rate factors for non-battery electrification components for different electrified powertrains.

[587] Islam, E. S. et al. 2020. Energy Consumption and Cost Reduction of Future Light-Duty Vehicles through Advanced Vehicle Technologies: A Modeling Simulation Study Through 2050. Contract ANL/ESD-19/10. Available at: https://publications.anl.gov/anlpubs/2020/08/161542.pdf. (Accessed: Feb. 12, 2024).

[588] Islam, E. S. et al. 2021. A Detailed Vehicle Modeling & Simulation Study Quantifying Energy Consumption and Cost Reduction of Advanced Vehicle Technologies Through 2050 Department of Energy. Available at: https://www.osti.gov/biblio/1866349. (Accessed: Feb. 12, 2024).

Table 3-88: Learning Rate Factor Used for Non-Battery Electrification Components for Electrified Powertrains (MYs 2017-2033)

Technology	Model Year															
	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
SS12V	0.8914	0.8634	0.8374	0.8143	0.7921	0.7734	0.7565	0.7423	0.7299	0.7190	0.7093	0.7006	0.7006	0.6988	0.6971	0.6953
BISG	0.7849	0.7312	0.6882	0.6559	0.6344	0.6129	0.5914	0.5806	0.5591	0.5484	0.5376	0.5376	0.5269	0.5256	0.5243	0.5229
P2D, P2SGDID, P2S, P2SGDIS, P2TRB0, P2TRBE, P2TRB1, P2TRB2, P2HCR, P2HCRE, SHEVPS	0.8925	0.8710	0.8387	0.8172	0.7849	0.7634	0.7419	0.7312	0.7204	0.7097	0.6989	0.6882	0.6882	0.6846	0.6810	0.6775
PHEV20T, PHEV50T, PHEV20H, PHEV50H, PHEV20PS, PHEV50PS	0.8791	0.8462	0.8132	0.7802	0.7582	0.7253	0.7033	0.6923	0.6703	0.6593	0.6593	0.6484	0.6374	0.5937	0.5511	0.5095
BEV1, BEV2, BEV3, BEV4	0.8276	0.7701	0.7241	0.6897	0.6437	0.6092	0.5862	0.5632	0.5517	0.5287	0.5172	0.5172	0.5057	0.4931	0.4808	0.4688
FCEV	0.9212	0.8950	0.8807	0.8665	0.8522	0.8379	0.8280	0.8181	0.8081	0.7982	0.7882	0.7783	0.7684	0.7491	0.7304	0.7122

Table 3-89: Learning Rate Factor Used for Non-Battery Electrification Components for Electrified Powertrains (MYs 2034-2050)

Technology	Model Year														
	2036	2037	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
SS12V	0.6936	0.6919	0.6901	0.6884	0.6867	0.6850	0.6833	0.6816	0.6799	0.6782	0.6765	0.6748	0.6731	0.6714	0.6697
BISG	0.5216	0.5203	0.5190	0.5177	0.5164	0.5151	0.5139	0.5126	0.5113	0.5100	0.5087	0.5075	0.5062	0.5049	0.5037

P2D, P2SGDID, P2S, P2SGDIS, P2TRB0, P2TRBE, P2TRB1, P2TRB2, P2HCR, P2HCRE, SHEVPS	0.6740	0.6704	0.6669	0.6634	0.6599	0.6564	0.6529	0.6494	0.6460	0.6425	0.6390	0.6356	0.6322	0.6287	0.6253
PHEV20T, PHEV50T, PHEV20H, PHEV50H, PHEV20PS, PHEV50PS	0.4893	0.4693	0.4495	0.4300	0.4204	0.4108	0.4013	0.3919	0.3881	0.3843	0.3806	0.3769	0.3732	0.3695	0.3658
BEV1, BEV2, BEV3, BEV4	0.4629	0.4571	0.4514	0.4458	0.4430	0.4402	0.4374	0.4347	0.4336	0.4325	0.4315	0.4304	0.4293	0.4282	0.4272
FCEV	0.7033	0.6945	0.6858	0.6772	0.6730	0.6688	0.6646	0.6604	0.6588	0.6571	0.6555	0.6539	0.6522	0.6506	0.6490

3.3.5.4. Total Electrified Powertrain Costs

For this analysis, we calculate total electrified powertrain costs by summing individual component costs, which ensures that all technologies in an electrified powertrain appropriately contribute to the total system cost. We combine the costs associated with the IC engine (if applicable) and transmission, non-battery electrification components like the electric machine, and battery pack to create a full-system cost. The following subchapters describe how we calculate the aggregated cost of each electrified powertrain based on the detailed component costs presented in the earlier subchapters.

The application of the electrification costs to an existing platform follows the same basic process for each technology on the electrification path. The costs for each technology depend on the model year that the CAFE Model applies the technology. First, the model must remove costs associated with reference powertrain technologies. Next, the model applies the costs associated with the electrification technology, discussed above.

The incremental costs for these electrification technologies can be found in three places: the "Engines" tab and "Vehicles" tab of the Technologies Input File, and the CAFE Model Battery Costs File, which is the database of battery costs DMCs created using the BatPaC model. Table 3-90 shows a summary of the general components considered for each electrification technology and where the costs of those components can be found in the CAFE Model Input File folders.

Table 3-90: Breakdown of the Component Costs Considered in the CAFE Analysis

Electrification Technology Type	Technologies Input File; Vehicle Tabs	Technologies Input File; Engine Tabs	CAFE Model Battery Costs File[589]
Micro Hybrid (SS12V)	Motor/generator	N/A	Battery pack[590]
Mild Hybrid (BISG)	Motor/generator, DC/DC converter, power electronics, cables, and other components	N/A	Battery pack
Strong Hybrid with Parallel Architecture (P2)	DC/DC converter, high voltage cables, motor/generator, AT8L2 transmission, and power electronics	IC engine*	Battery pack
Strong Hybrid with Power-Split Device (SHEVPS)	DC/DC converter, high voltage cables, motor/generator, eCVT transmission, and power electronics	IC engine	Battery pack
Plug-in Hybrid with Parallel Architecture and Turbo Engine (PHEV 20T/50T)	DC/DC converter, on-board charger, high voltage cables, motor/generator, AT8L2 transmission, and power electronics	IC engine	Battery pack
Plug-in Hybrid with Parallel Architecture and HCR Engine (20H/50H)	DC/DC converter, on-board charger, high voltage cables, motor/generator, AT8L2	IC engine	Battery pack

[589] The CAFE Model Battery Costs File is installed as part of the CAFE Model installation and is viewable in the CAFE Model Program Directory.
[590] As discussed further in this chapter, we no longer use the BatPaC SS12V battery cost and use a cheaper AGM battery instead, and the updated cost is reflected in the CAFE Model Battery Costs File.

	transmission, and power electronics		
Plug-in Hybrid with Power-Split Device and Atkinson Cycle Engine (PHEV 20/50)	DC/DC converter, on-board charger, high voltage cables, motor/generator, eCVT, transmission, and power electronics	IC engine	Battery pack
Battery Electric (BEVs)	DC/DC converter, on-board charger, high voltage cables, motor/generator, direct drive transmission, power electronics	ETDS, see Table 3-83 for detail	Battery pack
Fuel Cell Electric (FCEV)	Fuel cell system, high voltage cables, motor/generator, H2 tank, transmission, and power electronics	N/A	Battery pack

*The engine cost for a P2 Hybrid is based on engine technology used in the CONV.

The following subchapters discuss how the costs of each component are aggregated to create a total electrified powertrain cost.

3.3.5.4.1. Micro Hybrid Cost

As discussed earlier in Chapter 3.3.4, micro hybrid-electric vehicle SS12V technology does not provide any propulsion assistance, thus there is no cost associated with the SS12V system under the Engine tabs of the Technologies Input File. In the vehicle class tabs in the Technologies Input File, there is a fixed cost listed for SS12V that covers the battery and non-battery components in the system.

The SS12V battery cost, as with the model year 2024-2026 rule, reflects the cost of the absorbed-glass-mat (AGM) battery chemistry. The battery pack direct manufacturing costs for SS12V systems is $113, across all vehicle classes, as shown in Table 3-91 below. This cost also more closely aligns with the cost of the SS12V system presented in the 2015 NAS report.[591]

Unlike the rest of the electrification technologies, the micro hybrid system uses a shallower learning curve, as shown in Chapter 3.3.5.2. This shallow curve reflects the maturity of the technology; as we discuss in Chapter 3.3.2, over 50 percent of the model year 2022 fleet utilizes a SS12V micro hybrid system.

Table 3-91 lists the cost of the SS12V system and battery for different vehicle classes. For the SS12V electrified powertrain, the Technologies Input File contains the cost of the non-battery components with RPE and learning, as well as learning factor for the battery for each vehicle class.

Table 3-91: MY 2022 SS12V Total Cost for All Vehicle Classes in 2021$

	Small Car	Medium Car	Small SUV	Medium SUV	Pickup (LD)	Pickup (HDPUV)	Van (HDPUV)
Non-battery Component DMC	$171.55	$171.55	$171.55	$171.55	$171.55	$171.55	$171.55
Non-battery Component Cost in 2022 with RPE and Learning	$215.47	$215.47	$215.47	$215.47	$215.47	$215.47	$215.47

[591] 2015 NAS report, at 158.

Battery Pack DMC	$113.00	$113.00	$113.00	$113.00	$113.00	$113.00	$113.00
Battery Pack Cost in 2022 with RPE and Learning	$163.13	$163.13	$163.13	$163.13	$163.13	$163.13	$163.13
Total System Cost in 2022	$378.60	$378.60	$378.60	$378.60	$378.60	$378.60	$378.60

3.3.5.4.2. Mild Hybrid Cost

For this analysis, we use a fixed cost for a mild hybrid-electric vehicle BISG system; the total cost for the BISG system is the sum of non-battery component costs from the Technologies Input File and the batteries from the CAFE Model Battery Costs File. The vehicle class tabs in the Technologies Input File provide a non-battery component cost that includes the DMC, RPE, and a learning factor applied to battery cost. Note that the Technologies Input File includes the battery cost with the learning rate applied, while the CAFE Model Battery Costs File provides only the battery DMC for model year 2022 (in 2021$). To determine the total cost of the system for a vehicle, the vehicle technology class's technology key must align between the two files.

Table 3-92 below shows how costs are added to create the total BISG system cost. As an example, the model year 2022 medium car BISG cost of $627.00 can be found on the 'MedCar' tab in the Technologies Input File. This cost includes a learning rate specific to the non-battery components, as well as RPE. The medium car BISG cost of $294.46 found in the CAFE Model Battery Costs File is a DMC multiplied by 1.4436 from the Battery Cost Learning Rates Table (columns 'AT' and onward on the 'MedCar' tab), which is the product of 1.5 RPE and a learning factor of 0.9624 (because the base learning rate year for batteries is 2021), and that results in the total of $425.10. These two costs, which are both for model year 2022, sum to $1,052.10.

Table 3-92: Example of MY 2022 Mild Hybrid Total Cost for Different Vehicle Classes in 2021$

	Small Car	Medium Car	Small SUV	Medium SUV	Pickup (LD)	Pickup (HDPUV)	Van (HDPUV)
Non-battery Component DMC	$607.40	$607.40	$607.40	$607.40	$607.40	$607.40	$607.40
Cost in 2022 with RPE and Learning	$627.00	$627.00	$627.00	$627.00	$627.00	$627.00	$627.00
Battery Pack DMC	$294.46	$294.46	$294.46	$294.46	$294.46	$310.89	310.89
Battery Pack Cost in 2022 with RPE and Learning	$425.10	$425.10	$425.10	$425.10	$425.10	$448.82	$448.82
Total System Cost in 2022	$1,052.10	$1,052.10	$1,052.10	$1,052.10	$1,052.10	$1,075.82	$1,075.82

3.3.5.4.3. Strong Hybrid and Plug-in Hybrid Electric Vehicle Costs

In this analysis, the total cost for strong hybrid-electric vehicles includes the electric machine(s), battery pack, ICE, and transmission. Autonomie optimizes each strong hybrid powertrain for the given vehicle class by appropriately sizing these components.

SHEVP2 and SHEVPS have different architectures and powertrain characteristics, and, in turn, have different costs. We base the cost of SHEVP2 engines and transmissions on estimates discussed further in Chapter 3.1 and Chapter 3.2, respectively. The cost for SHEVP2 electric machines and battery packs are based on their sizes and are optimized by the Autonomie sizing algorithm discussed broadly in Chapter 3.3.4 as well as in detail in the CAFE Analysis Autonomie Documentation.[592] SHEVPS total powertrain costs include the optimized battery pack, electric machines, HCR1 engine, and eCVT. Like SHEVP2, electric machine and battery pack costs are dependent on their optimized size from Autonomie for different vehicle classes.

As described in Chapter 3.3.5.2, the cost of non-battery hybrid system components also includes the cost of the traction motor, generator motor, power electronics (power inverter and DC/DC converter), high voltage cables and connectors; PHEVs include costs for the charging cord and on-board chargers. We use the cost of the AT8L2 transmission as a cost proxy for the hybrid transmission architecture in P2 hybrid systems. The costs shown here do not include the cost of the IC engine coupled to the hybrid system.

Since motor sizing varies based on road load levels, the average motor sizes act as a mid-range representation for motor ratings across all road load combinations. We use Autonomie simulations to compute the average rating for traction and generator motors across all road load combinations for SHEVPS and SHEVP2 vehicles. After calculating the average motor size, we multiply the motor size by the unit cost ($/kW) to get the overall DMC for both traction motors and generator motors, as explained in Chapter 3.3.5.2. The costs shown in the following tables are in 2021$.

We calculate the cost of plug-in hybrid vehicles similar to strong hybrids by using Autonomie to optimize plug-in-hybrid system components, as explained in Chapter 3.3.4; as described, we use one engine technology and one transmission technology per plug-in hybrid architecture type. We use these modeling results to determine costs as described in Chapters 3.3.5.1 and 3.3.5.2.

For PHEVs that follow SHEVP2 on the hybrid/electric architecture path, as shown in Chapter 3.3.1, we base the total costs on a PHEV system paired with a TURBO1 engine. We calculate the total cost for the powertrain by summing the costs of the TURBO1 engine, an AT8L2 transmission, and the battery and non-battery electrification technology components. For PHEVs that follow the SHEVP2 architecture but adopts an HCR engine instead, we calculate the total cost of the powertrain by summing the costs of HCR engine, an AT8L2 transmission, and the battery and non-battery electrification technology components. We calculate the total cost for PHEVs that follow the SHEVPS architecture in the hybrid/electric architecture path by summing the costs of the HCR1 engine, the CVTL2 transmission, and the sized battery pack and non-battery electrification technology components.

Table 3-93 and Table 3-94 show the overall cost of electrified powertrains for strong hybrids and PHEVs. Note that the battery cost is not broken out in a separate column in this table; however, the total electrification cost includes the cost of the battery. The total DMC of non-battery electrification components includes the costs of motor and motor/generator (when applicable), DC/DC converter, cables, and on-board charger (for PHEV only). For more details of these costs refer to Chapter 3.3.5.2.

[592] Chapter "Split HEV Sizing Algorithm" of the CAFE Analysis Autonomie Documentation.

Table 3-93: Cost Estimation for Hybrid and Plug-in Hybrid Electric Drivetrains for the Medium Car and Small SUV Non-Performance Vehicle Technology Classes in 2022 (in 2021$)[593]

Electric Powertrain	Traction Motor (Peak Power) [kW]	Traction Motor DMC [2021$]	Motor Generator (Continuous Power) [kW]	Motor Generator DMC [2021$]	ETDS (Motor and Inverter) DMC [2021$]	DC/DC Converter [kW]	DC/DC Converter [2021$]	Onboard Charger [kW]	Onboard Charger [2021$]	Power Distribution Cables [2021$]	Electrical Component DMC [2021$]	Electrical Component Total Costs [2021$]	Transmission Total Costs [2021$]	Non-Battery Electrification Total Costs [2021$]
Medium Car – Non-Performance														
Par HEV Turbo0 (P2TRB0)	28.24	$559.28	0	$0.00	$559.28	2	$201.87	0	$0.00	$180.44	$941.59	$1,185	$2,605	$3,789
Split HEV (SHEVPS)	85.19	$1,687	44.27	$876.57	$2,563	2	$201.87	0	$0.00	$180.44	$2,946	$3,706	$1,736	$5,442
Par PHEV20T (PHEV20T)	90.72	$1,796	0	$0.00	$1,796	2	$201.87	2	$187.07	$495.21	$2,681	$3,270	$2,605	$5,874
Par PHEV50T (PHEV50T)	95.83	$1,898	0	$0.00	$1,898	2	$201.87	2	$187.07	$495.21	$2,782	$3,393	$2,605	$5,998
Par PHEV20H (PHEV20H)	90.72	$1,796	0	$0.00	$1,796	2	$201.87	2	$187.07	$495.21	$2,681	$3,270	$2,605	$5,874
Par PHEV50H (PHEV50H)	95.83	$1,898	0	$0.00	$1,898	2	$201.87	2	$187.07	$495.21	$2,782	$3,393	$2,605	$5,998
Split PHEV20 (PHEV20PS)	97.03	$1,921	45.78	$906.61	$2,828	2	$201.87	2	$187.07	$495.21	$3,712	$4,528	$2,742	$7,270
Split PHEV50 (PHEV50PS)	116.87	$2,314	50.93	$1,009	$3,323	2	$201.87	2	$187.07	$495.21	$4,207	$5,132	$2,742	$7,874
Small SUV – Non-Performance														
Par HEV Turbo0 (P2TRB0)	28.36	$561.67	0	$0.00	$561.67	2	$201.87	0	$0.00	$180.44	$943.98	$1,188	$2,605	$3,792

[593] Numbers in this table are rounded.

Split HEV (SHEVPS)	93.14	$1,844	47.30	$936.67	$2,781	2	$201.87	0	$0.00	$180.44	$3,163	$3,980	$1,736	$5,716
Par PHEV20T (PHEV20T)	97.95	$1,940	0	$0.00	$1,940	2	$201.87	2	$187.07	$495.21	$2,824	$3,444	$2,605	$6,049
Par PHEV50T (PHEV50T)	103.46	$2,049	0	$0.00	$2,049	2	$201.87	2	$187.07	$495.21	$2,933	$3,577	$2,605	$6,182
Par PHEV20H (PHEV20H)	97.95	$1,940	0	$0.00	$1,940	2	$201.87	2	$187.07	$495.21	$2,824	$3,444	$2,605	$6,049
Par PHEV50H (PHEV50H)	103.46	$2,049	0	$0.00	$2,049	2	$201.87	2	$187.07	$495.21	$2,933	$3,577	$2,605	$6,182
Split PHEV20 (PHEV20PS)	104.63	$2,072	48.95	$969.28	$3,041	2	$201.87	2	$187.07	$495.21	$3,925	$4,788	$2,742	$7,530

Table 3-94: Cost Estimation for Hybrid and Plug-in Hybrid Electric Drivetrains for the Medium Car and Small SUV Performance Vehicle Technology Classes in 2022 (in 2021$)[594]

Electric Powertrain	Traction Motor (Peak Power) [kW]	Traction Motor DMC [2021$]	Motor Generator (Continuous Power) [kW]	Motor Generator DMC [2021$]	ETDS (Motor and Inverter) DMC [2021$]	DC/DC Converter [kW]	DC/DC Converter [2021$]	Onboard Charger [kW]	Onboard Charger [2021$]	Power Distribution Cables [2021$]	Electrical Component DMC [2021$]	Electrical Component Total Costs [2021$]	Transmission Total Costs [2021$]	Non-Battery Electrification Total Costs [2021$]
Medium Car – Performance														
Par HEV Turbo0 (P2TRB0)	29.83	$590.78	0	$0.00	$590.78	2	$201.87	0	$0.00	$180.44	$973.09	$1,224	$2,605	$3,829
Split HEV (SHEVPS)	118.85	$2,353	61.39	$1,216	$3,569	2	$201.87	0	$0.00	$180.44	$3,951	$4,971	$1,736	$6,707
Par PHEV20T (PHEV20T)	94.98	$1,881	0	$0.00	$1,881	2	$201.87	2	$187.07	$495.21	$2,765	$3,373	$2,605	$5,977

[594] Numbers in this table are rounded.

Par PHEV50T (PHEV50T)	99.91	$1,978	0	$0.00	$1,978	2	$201.87	2	$187.07	$495.21	$2,863	$3,492	$2,605	$6,096
Par PHEV20H (PHEV20H)	94.98	$1,881	0	$0.00	$1,881	2	$201.87	2	$187.07	$495.21	$2,765	$3,373	$2,605	$5,977
Par PHEV50H (PHEV50H)	99.91	$1,978	0	$0.00	$1,978	2	$201.87	2	$187.07	$495.21	$2,863	$3,492	$2,605	$6,096
Split PHEV20 (PHEV20PS)	119.49	$2,366	63.37	$1,254.87	$3,621	2	$201.87	2	$187.07	$495.21	$4,505	$5,495	$2,742	$8,238
Split PHEV50 (PHEV50PS)	168.48	$3,336	69.86	$1,383.35	$4,720	2	$201.87	2	$187.07	$495.21	$5,604	$6,835	$2,742	$9,578
Small SUV – Performance														
Par HEV Turbo0 (P2TRB0)	30.39	$601.83	0	$0.00	$601.83	2	$201.87	0	$0.00	$180.44	$984.14	$1,238	$2,605	$3,843
Split HEV (SHEVPS)	114.92	$2,276	56.9	$1,126.85	$3,403	2	$201.87	0	$0.00	$180.44	$3,785	$4,762	$1,736	$6,497
Par PHEV20T (PHEV20T)	102.87	$2,037	0	$0.00	$2,037	2	$201.87	2	$187.07	$495.21	$2,921	$3,563	$2,605	$6,168
Par PHEV50T (PHEV50T)	108.27	$2,144	0	$0.00	$2,144	2	$201.87	2	$187.07	$495.21	$3,028	$3,694	$2,605	$6,298
Par PHEV20H (PHEV20H)	102.87	$2,037	0	$0.00	$2,037	2	$201.87	2	$187.07	$495.21	$2,921	$3,563	$2,605	$6,168
Par PHEV50H (PHEV50H)	108.27	$2,144	0	$0.00	$2,144	2	$201.87	2	$187.07	$495.21	$3,028	$3,694	$2,605	$6,298
Split PHEV20 (PHEV20PS)	118.22	$2,341	58.84	$1,165.17	$3,506	2	$201.87	2	$187.07	$495.21	$4,390	$5,355	$2,742	$8,097
Split PHEV50 (PHEV50PS)	149.48	$2,960	64.45	$1,276.21	$4,236	2	$201.87	2	$187.07	$495.21	$5,120	$6,246	$2,742	$8,988

3.3.5.4.4. Battery Electric Vehicle Cost

For this analysis, the total costs of BEVs include the optimized battery pack and electric machine costs. Like the other electrified powertrains, Autonomie optimizes both the size of the battery pack and electric machine to fulfill the performance requirements for each vehicle. Further discussion of electrification technology component sizing and optimization is provided in Chapter 3.3.4. Electrification component costing is discussed in Chapters 3.3.5.1 and 3.3.5.2.

The model calculates the total cost of a BEV by first removing the cost of the ICE and transmission associated with the conventional or hybridized powertrain and replacing that cost with the cost of an ETDS (i.e., the motor and inverter). It is important to accurately estimate the motor size (rating) because the cost of the ETDS accounts for a significant portion of the total cost of electrifying a vehicle. We used the model year 2020 Market Data Input File to compute the average engine power for each technology class. Table 3-95 shows the steps taken to calculate the equivalent electric motor power required to replace each engine technology, derived from the model year 2020 Market Data Input File.[595] These power ratings can be found under appropriate Engine tabs in the Technologies Input File. The cost of the rest of the non-battery electrification components can be found under the vehicle tabs of the Technologies Input File. Summing these two costs leads to the total BEV electrified powertrain cost shown in the final column of Table 3-95 and Table 3-96. The values in these tables are for DMC year 2022 in 2021$.

[595] We found that model year 2022 vehicles' power ratings were similar to model year 2020 vehicles and concluded the analysis based on the model year 2020 fleet was still appropriate.

Table 3-95: Cost Estimation for Battery Electric Drivetrains for LD Engine Technology Classes in 2022 (in 2021$)

Technology Class	HP Estimate	Power [kW]	ETDS (Motor and Inverter) DMC [2021$]	ETDS (Motor and Inverter) Total Costs [2021$]	DC/DC Converter [kW]	DC/DC Converter [2021$]	Onboard Charger [kW]	Onboard Charger [2021$]	Power Distribution Cables [2021$]	Other Non-Battery Electrical Component DMC [2021$]	Other Non-Battery Electrical Component Total Costs [2021$]	BEV Electrification Total Costs [2021$]
3C1B	122	91.0	$1,802.02	$1,957.37	2.0	$ 201.87	7.0	$654.76	$495.21	$1,351.84	$1,468.38	$3,425.75
4C1B	198	147.5	$2,920.85	$3,172.65	2.0	$ 201.87	7.0	$654.76	$495.21	$1,351.84	$1,468.38	$4,641.03
6C1B	255	190.1	$3,764.43	$4,088.95	2.0	$ 201.87	7.0	$654.76	$495.21	$1,351.84	$1,468.38	$5,557.33
6C2B	286	212.9	$4,215.92	$4,579.36	2.0	$ 201.87	7.0	$654.76	$495.21	$1,351.84	$1,468.38	$6,047.74
8C2B	286	212.9	$4,215.92	$4,579.36	2.0	$ 201.87	7.0	$654.76	$495.21	$1,351.84	$1,468.38	$6,047.74

Table 3-96: Cost Estimation for Battery Electric Drivetrains for HDPUV Engine Technology Classes in 2022 (in 2021$)

Technology Class	HP Estimate	Power [kW]	ETDS (Motor and Inverter) DMC [2021$]	ETDS (Motor and Inverter) Total Costs [2021$]	DC/DC Converter [kW]	DC/DC Converter [2021$]	Onboard Charger [kW]	Onboard Charger [2021$]	Power Distribution Cables [2021$]	Other Non-Battery Electrical Component DMC [2021$]	Other Non-Battery Electrical Component Total Costs [2021$]	BEV Electrification Total Costs [2021$]
4C1B_2b3	198	147.5	$2,920.85	$3,172.65	2.0	$201.87	11.0	$1,028.91	$495.21	$1,725.99	$1,874.78	$5,047.43
6C1B_2b3	255	190.1	$3,764.43	$4,088.95	2.0	$201.87	11.0	$1,028.91	$495.21	$1,725.99	$1,874.78	$5,963.73
6C2B_2b3	286	212.9	$4,215.92	$4,579.36	2.0	$201.87	11.0	$1,028.91	$495.21	$1,725.99	$1,874.78	$6,454.14
8C2B_2b3	369	275.4	$5,453.57	$5,923.71	2.0	$201.87	11.0	$1,028.91	$495.21	$1,725.99	$1,874.78	$7,798.49

3.3.5.4.5. Fuel Cell Electric Vehicle Cost

For this analysis, we consider technology advancements in fuel cell systems, hydrogen storage tanks and hydrogen delivery systems, sensors and control systems, and market penetration. The cost of hydrogen storage tanks and fuel cells come from a Department of Energy (DOE), Office of Energy Efficiency and Renewable Energy (EERE), Fuel Cell Technologies Office cost analysis. In these studies, DOE estimates the cost for 10,000 units per year production of a compressed gas storage system at around $26/kWh (2016$, equivalent to $29.18 in 2021), and the cost of the fuel cell system at about $85/kW (2017$, equivalent to $93.61 in 2021).[596,597] The DMC for FCEVs in this analysis is $13,674,89 in 2021$. After RPE, the cost is $19,432,22 in 2020 in 2021$.

The total cost of an FCEV includes the fuel cell, control systems, motors, inverters, hydrogen storage tanks, wiring harness, hydrogen fuel delivery lines, sensors, and hardware. See the vehicle tabs in the Technologies Input File for the total cost of the FCEV in this analysis across model years.

3.4. Mass Reduction Paths

Mass reduction is a relatively cost-effective means of improving fuel economy, and vehicle manufacturers are expected to apply various MR technologies to meet fuel economy standards. Vehicle manufacturers can reduce vehicle mass through several different techniques, such as modifying and optimizing vehicle component and system designs, part consolidation, and adopting materials that are conducive to MR (advanced high strength steel (AHSS), aluminum, magnesium, and plastics including carbon fiber reinforced plastic (CFRP).

The cost for MR depends on the type and amount of materials used, the manufacturing and assembly processes required, and the degree to which manufacturers need to make changes to plants and new manufacturing and assembly equipment. In addition, manufacturers may develop expertise and invest in certain MR strategies that may affect the approaches for MR they consider and the associated costs. Manufacturers must also consider vehicle attributes like NVH, ride quality, handling, crash safety, repairability, and various acceleration metrics when considering how to implement any MR strategy. These are considered to be aspects of performance, and for this analysis any identified pathways to compliance are intended to maintain performance neutrality. Therefore, we do not consider MR via elimination (de-contenting) of, for example, luxury items such as climate control, or interior vanity mirrors, leather padding, etc., in the MR pathways for this analysis.

The automotive industry uses different metrics to measure vehicle weight. Some commonly used measurements are vehicle curb weight,[598] GVW,[599] GVWR,[600] GCVW,[601] and equivalent test weight (ETW),[602] among others. The vehicle curb weight is the most commonly used measurement when comparing vehicles' weights. A vehicle's curb weight is the weight of the vehicle including fluids, but without a driver, passengers, and cargo. A vehicle's glider weight, which is vehicle curb weight minus the powertrain weight, is used in the CAFE analysis to track the potential opportunities for weight reduction not including the powertrain. A glider's subsystems may consist of the vehicle body, chassis, interior, steering, electrical accessory, brake, and wheels systems. The percentage of weight assigned to the glider is dependent on the composition of the initial analysis fleet used for any given CAFE rule analysis. For example, as BEVs with their EMs, batteries, inverters, etc. become a greater percentage of the fleet, glider weight percentage will change compared to earlier fleets which had higher dominance of ICE powertrains. Therefore, in going from fleets dominated by

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[596] James, B. et al. 2016. Hydrogen Storage System Cost Analysis. Final Report. at 20 -Table 6.Available at: https://www.osti.gov/servlets/purl/1343975. (Accessed: Feb. 12, 2024).
[597] Thompson, S. et al. 2018. Direct Hydrogen Fuel Cell Electric Vehicle Cost Analysis: System and High-Volume Manufacturing Description, Validation, and Outlook. at 8 – Fig. 6. Available at: https://www.osti.gov/pages/biblio/1489250. (Accessed: May 31, 2023).
[598] This is the weight of the vehicle with all fluids and components but without the drivers, passengers, and cargo.
[599] This weight includes all cargo, extra added equipment, and passengers aboard.
[600] This is the maximum total weight of the vehicle, passengers, and cargo to avoid damaging the vehicle or compromising safety.
[601] This weight includes the vehicle and a trailer attached to the vehicle, if used.
[602] For the EPA two-cycle regulatory test on a dynamometer, an additional weight of 300 lbs. is added to the vehicle curb weight. This additional 300 lbs. represents the weight of the driver, passenger, and luggage. Depending on the final test weight of the vehicle (vehicle curb weight plus 300 lbs.), a test weight category is identified using the table published by EPA according to 40 CFR 1066.805. This test weight category is called "Equivalent Test Weight" (ETW).

ICEs to subsequent fleets dominated by battery electric powertrains, the glider percent share will decrease because BEV powertrains weigh more than ICE powertrains, and this would be reflected in the rule associated with that fleet.

For the light-duty fleet portion of this analysis, we considered five levels of MR technology (MR1-MR5) that include increasing amounts of advanced materials and MR techniques applied to the glider. We accounted for mass changes associated with powertrain changes separately. Glider MR can sometimes enable a smaller engine while maintaining performance neutrality. Smaller engines typically weigh less than bigger ones. We captured any changes in the resultant fuel savings associated with powertrain MR and downsizing via the Autonomie simulation. Autonomie calculates a hypothetical vehicle's theoretical fuel mileage using a MR to the vehicle curb weight equal to the sum of mass savings to the glider plus the mass savings associated with the downsized powertrain.

Costs for the five levels of MR are the same as those used in the model years 2024-2026 final rule. The costs for the fifth level of MR (MR5) technology are based on vehicle MR design concept studies, teardown studies, and the NAS 2021 report. The incremental increase in price is not linear going from MR1 to MR5. Rather, the costs increase in a quasi-exponential fashion. This is because as more mass is removed, there is a necessity to employ more and more expensive materials and processes to realize further levels of MR. These costs consider both primary and secondary MR opportunities and MR of primary versus secondary structure, all of which are discussed further later in this chapter. In addition, the following subchapters discuss the assumptions for the five MR technology levels, the process used to assign initial analysis fleet MR assignments, the effectiveness for applying MR technology, and MR costs.

Note that in previous rules, there was a sixth level of MR available as a pathway to compliance. For this analysis, this pathway was removed because it relied on extensive use of carbon fiber composite technology to an extent that is only found in purpose-built racing cars and a few hundred road legal sports cars costing hundreds of thousands of dollars. We determined that this technology is simply too expensive for use in attainable vehicles for typical consumers. Furthermore, there is simply too much competition among industries to obtain a scarce resource: raw carbon fibers. Given the relative scarcity of raw carbon fiber,[603] the laws of supply and demand dictate that any earnest attempt by a high-volume manufacturer to produce one of their most popular models using enough carbon fiber to reach the sixth MR level would trigger rapid materials cost increases. There are constant efforts at the national laboratory, university, and industry levels to produce low cost, plentiful carbon fiber. We continue to monitor these efforts and with real innovation in this space would consider adding back the sixth level of MR pathway.

Given the inclusion of the HDPUV fleet in this rule, MR as a pathway to compliance must be analyzed separately. The reason for this is that the vehicles within the heavy-duty fleets are built for a very different duty cycle[604] and tend to be larger and heavier. Moreover, there are different vehicle parameters, like towing capacity, that drive vehicle mass in the heavy-duty fleet rather than, for example, NVH (noise, vibration, and harshness) performance in the light-duty fleet.

For the heavy-duty fleet we considered two levels of MR (MR1 – MR2) and a base level (MR0). As with the light-duty fleet, within the CAFE Model we only consider the glider share of the vehicle's mass. The powertrain mass is dealt with inside of the Autonomie model. Due to the lack of data regarding recent (2020-2022) heavy fleets, the reference fleet used to gauge MR in this analysis is made up of a hybrid of previous fleets going as far back as 2016. Because the application of lightweighting technology in the heavy-duty fleets has not advanced as quickly as for the light-duty fleet,[605] using a hybrid fleet provides good correlation regardless.

[603] Sloan, J. 2020. Carbon Fiber Suppliers Gear up for Next-Gen Growth. Last revised: Feb. 11, 2020. Available at: https://www.compositesworld.com/articles/carbon-fiber-suppliers-gear-up-for-next-gen-growth. (Accessed: Feb. 12, 2024).

[604] heavy-duty vans that are used for package delivery purposes are frequently loaded to GVWR. However, light-duty passenger cars are never loaded to GVWR. Operators of heavy-duty vans have an economic motivation to load their vehicles to GVWR. In contrast studies show that between 38% and 82% of passenger cars are used soley to transport their drivers. (Bureau of Transportation Studies, 2011, Federal Highway Administration (FHWA) Publication No. FHWA-PL-18-020, 2019).

[605] Consider that the first pickup in the heavy-duty fleet that had a primary structure mostly made from aluminum was the Ford F-250 in 2017. However, the first vehcile in the light-duty fleet that had a primary structure mainly made from aluminum was the Audi A8 in 1994.

Costs used for MR1 MR technology for the heavy-duty fleet mirror those used for MR1 for the light-duty fleet. Since MR2 for the heavy-duty fleet is consistent with MR between MR4 and MR5 for the light-duty fleet, cost numbers for MR technology used herein are derived using linear extrapolation from the light-duty fleet MR4 and MR5 prices.

3.4.1. Mass Reduction in the CAFE Model

The amount of MR technology existing in a given vehicle platform or applied to a given platform to meet compliance is expressed in terms of CAFE MR (MR) levels, or MR plus a number ranking. For the light-duty fleet, this is accomplished with five levels (MR0 – MR5) and with two levels (MR0 – MR2) for the heavy-duty fleet. For this analysis, we considered MR opportunities from the glider subsystems of a vehicle first, and then considered associated opportunities to downsize the powertrain, which we accounted for separately.[606] As explained below, in the Autonomie simulations the glider includes the body, chassis, interior, electrical accessories, steering, brakes and wheels, which encompass both primary and secondary systems that the model can light-weight. In this analysis, we assumed the glider share is 71 percent of vehicle curb weight. Autonomie sizes the powertrain based on the glider weight and the mass of some of the powertrain components in an iterative process. The mass of the powertrain depends on the powertrain size. Therefore, the weight of the glider impacts the weight of the powertrain.[607]

We used glider weight to apply non-powertrain MR technology in the CAFE Model and used Autonomie simulations to determine the size of the powertrain and corresponding powertrain weight for the respective glider weight. The combination of glider weight (after MR) and re-sized powertrain weight equal the vehicle curb weight. The cost and fuel savings effectiveness calculation for curb weight MR (described in a subsequent subchapters) occurs within Autonomie. The Autonomie simulation takes into account both glider MR and powertrain MR in its calculations of a vehicle's fuel mileage.

3.4.1.1. Assumptions Behind the LD Mass Reduction Levels

The light-duty analysis considers five levels of MR technologies that light-duty manufacturers could use to comply with CAFE standards. The magnitude of MR in percent for each of these levels is shown in Table 3-97 as a percentage of vehicle glider weight (71%[608] shown in the table) and curb weight for both passenger cars and light trucks.

Table 3-97: Mass Reduction Technology Level and Associated Glider and Curb Mass Reduction

MR Level	Percent Glider Weight Reduction	Percent Vehicle Curb Weight (Passenger Cars) Reduction	Percent Vehicle Curb Weight (Light Trucks) Reduction
MR0	0%	0.00%	0.00%
MR1	5%	3.55%	3.55%
MR2	7.5%	5.33%	5.33%
MR3	10%	7.10%	7.10%
MR4	15%	10.65%	10.65%
MR5	20%	14.20%	14.20%

While there are a range of MR technologies that manufacturers can apply to vehicles to achieve each of the five MR levels, there are some general trends that are helpful to illustrate the more widely used approaches.

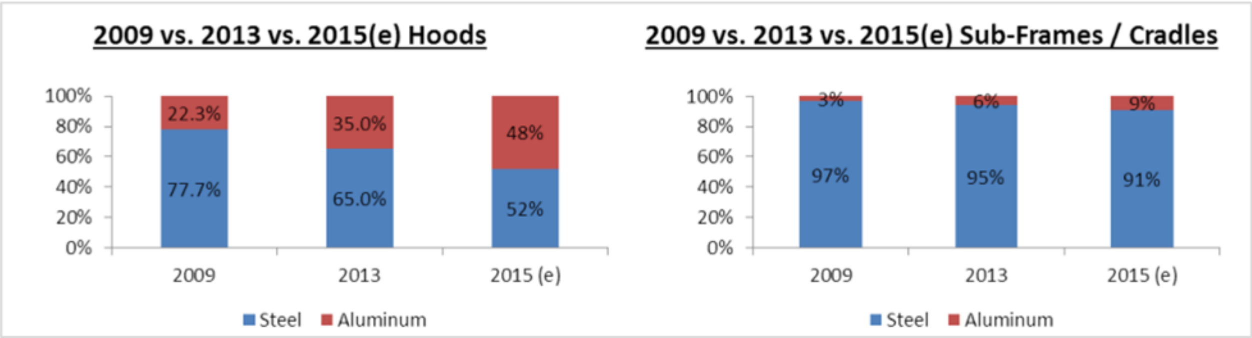
[606] When the mass of the vehicle is reduced by an appropriate amount, the engine may be downsized to maintain performance. See Chapter 2.3.4 for more details.
[607] Since powertrains are sized based on the glider weight for the analysis, glider weight reduction beyond a threshold amount during a redesign will lead to re-sizing of the powertrain. For the analysis, the glider was used as a base for the application of any type of powertrain. A CONV consists of an engine, transmission, exhaust system, fuel tank, radiator, and associated components. A hybrid powertrain also includes a battery pack, EM(s), generator, high voltage wiring harness, high voltage connectors, inverter, battery management system(s), battery pack thermal system, and EM thermal system.
[608] A 71% glider share is based on the average proportion of non-powertrain weight in an average passenger car and average LT.

Typically, MR0 reflects vehicles with widespread use of low carbon steel structures and body panels, and very little or no use of high-strength steel or aluminum. MR0 reflects materials in use for average vehicles in the model year 2022 timeframe. MR1-MR3 can be achieved with a steel body structure. In going from MR1 to MR3, expect low carbon steel to be replaced by high strength and then AHSS. In going from MR3 to MR4 light metals like aluminum and magnesium are required. This will start with using aluminum closure panels and then to get to MR4 the vehicle's primary structure will need to be mostly made from aluminum. In the majority of cases, carbon fiber technology used in close-out panels like roofs and door skins is necessary to reach MR5, perhaps with a mix of some aluminum and/or magnesium. Getting several percentage points MR past MR5 in anything resembling a passenger vehicle requires nearly every structural component be made from carbon fiber composite materials. This means the primary body structure and all closure panels like hoods and door skins are wholly made from carbon fiber composite materials. There may be some use of aluminum in the suspension. Vehicles with such construction do exist but make up less than 1% of the US fleet. The only exception to this would have been the BMW i3 but production ceased in summer 2022.

As discussed further in Chapter 3.4.5, the cost studies that we use to generate cost curves assume mass can be reduced in levels that require different materials and different components to be utilized, in a specific order. Our MR levels are loosely based on those studies' conclusions about what materials and components are required for each percent of MR.

AHSS and aluminum (AL) have played a major role in recent years as materials used to reduce vehicle mass. The penetration rate of AHSS or AL depends on a number of factors such as vehicle redesign cycle timing, material availability, accompanying changes in manufacturing equipment, and changes in joining methods, among other things. A study conducted for the American Iron and Steel Institute shows the application of AHSS in vehicles increased from 81 lbs. on average in 2006 to 254 lbs. in 2015.[609]

Figure 3-33: Penetration of AL in Hoods and Sub-Frames/Cradles from 2009 to 2015



According to a study conducted for the Aluminum Association, AL content in vehicles increased from nearly 300 lbs. in 2005, to 394 lbs. in 2015, up from roughly 80 lbs. in 1975, and a little more than 150 lbs. in 1990.[610] Since the 1980s, many castings have migrated from cast iron to aluminum.[611] Figure 3-33 shows AL replacing steel in greater percentages in vehicle hoods, and AL beginning to penetrate sub-frames/engine cradles in small percentages.[612]

A 2017 report published by American Chemistry Council shows that while the overall share of plastics and polymer composites in vehicles have decreased by 0.1 percent in the last 10 years,[613] the share of AL has

[609] Abraham, A. 2015. Metallic Material Trends in the North American Light Vehicle. Last revised: Mar. 17, 2015. Available at: https://www.repairerdrivennews.com/wp-content/uploads/2015/06/Metallic-Material-Trends-in-North-American-Light-Vehicles.pdf. (Accessed: Feb. 12, 2024).
[610] Ducker Worldwide LLC. 2014. 2015 North American Light Vehicle Aluminum Content Study. Executive Summary. at 1-24. http://www.autonews.com/assets/PDF/CA95065611.PDF. (Accessed: Feb. 12, 2024).
[611] For instance, engine blocks and transmission cases are nearly universally aluminum in the model year 2016 fleet, but aluminum was rarely used in these applications prior to the 1990's.
[612] *Id.*
[613] After rapidly increasing in the 1960's through the 1990's.

increased by 2.3 percent.[614] The report also published data on material content in vehicles as shown in Table 3-98 and Table 3-99.

Table 3-98: Average Materials Content of U.S./Canada Light Vehicles (lbs./vehicle)

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Average Weight	4,081	4,103	4,046	3,953	3,960	4,007	3,896	3,900	3,928	3,991	4,026
Regular Steel	1,622	1,644	1,627	1,501	1,458	1,439	1,368	1,354	1,342	1,330	1,335
High- & Medium-Strength[615]	502	518	523	524	555	608	619	627	649	701	742
Stainless Steel	73	75	75	69	72	73	68	74	73	75	74
Other Steels	34	34	33	31	32	32	30	32	32	32	32
Iron Castings	331	322	253	206	242	261	270	271	278	268	249
Aluminum	323	319	316	324	338	344	349	355	368	395	410
Magnesium	10	10	11	11	11	12	10	10	10	10	11
Copper and Brass	67	66	71	71	74	73	71	70	68	67	66
Lead	39	41	44	42	41	39	35	35	36	35	35
Zinc Castings	10	9	9	9	9	9	8	8	8	8	8
Powder Metal	42	43	43	41	41	42	44	45	46	45	44
Other Metals[616]	5	5	5	5	5	5	5	5	4	5	5
Plastics/Polymer Composites	342	339	348	384	359	353	332	328	329	334	332
Rubber	198	192	204	245	228	223	205	198	196	198	199
Coatings	30	30	31	36	36	33	28	28	28	28	28
Textiles	47	46	48	58	56	50	49	50	49	45	44
Fluids and Lubricants	211	215	214	217	219	221	219	222	224	225	226
Glass	105	103	99	88	92	98	95	96	96	95	93
Other	89	92	91	90	92	93	91	92	93	95	92

[614] American Chemistry Council. 2017. Plastics and Polymer Composites in Light Vehicles. at 5. This article is available in the rulemaking docket at NHTSA-2021-0053-0011.

[615] Despite long lead times for material qualification of new metal alloys, medium and high strength steels have been and continue to be widely adopted in the automotive industry at a rapid pace. Advanced steel materials typically replace regular steel, and often compete with aluminum and composites in body systems.

[616] "Other Metals" are typically used sparingly in specialty applications in the auto industry, and these metals make up a small portion of total vehicle weight.

Table 3-99: Mass Reduction Technology Level and Associated Glider and Curb Mass Reduction for HDPUVs

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Regular Steel	39.7 %	40.1 %	40.2 %	38.0 %	36.8 %	35.9 %	35.1 %	34.7 %	34.2 %	33.3 %	33.2 %
High- & Medium-Strength	12.3 %	12.6 %	12.9 %	13.3 %	14.0 %	15.2 %	15.9 %	16.1 %	16.5 %	17.6 %	18.4 %
Stainless Steel	1.8%	1.8%	1.9%	1.7%	1.8%	1.8%	1.7%	1.9%	1.9%	1.9%	1.8%
Other Steels	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%
Iron Castings	8.1%	7.8%	6.3%	5.2%	6.1%	6.5%	6.9%	6.9%	7.1%	6.7%	6.2%
Aluminum	7.9%	7.8%	7.8%	8.2%	8.5%	8.6%	9.0%	9.1%	9.4%	9.9%	10.2 %
Magnesium	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.2%	0.2%	0.3%
Copper and Brass	1.6%	1.6%	1.7%	1.8%	1.9%	1.8%	1.8%	1.8%	1.7%	1.7%	1.6%
Lead	1.0%	1.0%	1.1%	1.1%	1.0%	1.0%	0.9%	0.9%	0.9%	0.9%	0.9%
Zinc Castings	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%
Powder Metal	1.0%	1.0%	1.1%	1.0%	1.0%	1.0%	1.1%	1.2%	1.2%	1.1%	1.1%
Other Metals	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
Plastics/Polymer Composites	8.4%	8.3%	8.6%	9.7%	9.1%	8.8%	8.5%	8.4%	8.4%	8.4%	8.3%
Rubber	4.8%	4.7%	5.1%	6.2%	5.8%	5.6%	5.3%	5.1%	5.0%	5.0%	4.9%
Coatings	0.7%	0.7%	0.8%	0.9%	0.9%	0.8%	0.7%	0.7%	0.7%	0.7%	0.7%
Textiles	1.2%	1.1%	1.2%	1.5%	1.4%	1.3%	1.3%	1.3%	1.2%	1.1%	1.1%
Fluids and Lubricants	5.2%	5.2%	5.3%	5.5%	5.5%	5.5%	5.6%	5.7%	5.7%	5.6%	5.6%
Glass	2.6%	2.5%	2.4%	2.2%	2.3%	2.4%	2.4%	2.5%	2.4%	2.4%	2.3%
Other	2.2%	2.2%	2.2%	2.3%	2.3%	2.3%	2.3%	2.4%	2.4%	2.4%	2.3%

Adding aluminum to a vehicle's primary and/or secondary structure is useful in reaching higher levels of MR. To reach MR5 it is sometimes necessary to manufacture close-out body panels such as door outer skins, roofs, deck lids, and floor pans from carbon fiber reinforced polymers.

3.4.1.2. Mass Reduction in Heavy-Duty Pickup Trucks and Heavy-Duty Vans

We also developed CAFE Model MR technology pathways for HDPUVs (pickups and vans in Class 2b and 3 weight classes) for this analysis.

The MR strategies used in heavy-duty pickup trucks closely follow those used in the light-duty pickup fleet. All heavy-duty pickup trucks in the fleet combine a ladder frame with a semi structural cab and bed structure. In all cases, the ladder frame is made from steel or AHSS. By volume, most of the cabs and beds are made from strain hardening aluminum alloys. Additional MR is achievable in this portion of the fleet using such technologies as leaf springs made of glass reinforced plastics, driveshafts made from aluminum or even carbon fiber composite materials, and other technologies. Given the high magnitude cyclic loading to which work vehicles are subject it is challenging to make suspension components from aluminum. Front control arms made from aluminum were used on certain GM models in previous years but were replaced with cast iron versions. However, no vehicles in the current heavy-duty pickup fleet use aluminum suspension control or axle components.

The MR strategies followed by heavy-duty cargo and passenger vans closely resemble those used in passenger minivans. Unit body construction is used for the body-in-white structure.[617] Compared to the light-duty van fleet extra cross members are incorporated to boost the strength of the loading floors. No OEMs in the heavy-duty cargo and passenger van fleets use aluminum construction for the body-in-white structures. However, in the case of chassis-cab vehicles, there are aftermarket (non-OEM) cab or cargo box structures used that are indeed made from aluminum or fiber glass. Such structures begin rearward of the back of the front row of seats and are not included in this analysis. Similar to heavy-duty pickups, MR is achieved in some cases through using glass fiber reinforced leaf springs. Using aluminum or composite materials from which to construct driveshafts is another potential pathway to reduced mass. Finally, the high magnitude cyclic loading associated with transporting heavy cargo makes it challenging to use aluminum components in the suspension. Consequently, suspension component made from aluminum are uncommon in the heavy-duty van fleet.

Relative to the light-duty passenger car fleet, the diversity of MR technology used in the HDPUV fleet is limited. For example, in the light-duty passenger car fleet MR has been addressed in many diverse ways. Some examples include a primary structure made from large aluminum castings (e.g., Tesla Model Y), closure panels made from carbon fiber composites, bumper beams made from carbon fiber (e.g., 2022 Corvette), wheels made from magnesium, suspension cast from aluminum, brake rotors made from ceramic matrix composites, and exhaust systems made from titanium. Although the use of aluminum in cab and bed structures is now common in heavy-duty trucks due to large scale volume deployments of this technology (e.g., Ford F-series pickups and GM Silverado pickups), some of these light-duty strategies do not translate well to heavy-duty applications. For example, using aluminum suspension control arms is a common way to reduce mass. It is used by BMW, Mercedes, Audi and others. However, this particular MR technology does not translate well to the heavy-duty fleet. This is because the heavier absolute vehicle masses of heavy-duty vehicle result in higher loads on suspension components. Because aluminum is not as strong nor as fatigue resistant as the traditional steel technology used in these applications, aluminum suspension arms must be designed with larger dimensions to make up for the lower mechanical properties. However, there may not be enough room to package the larger component in the heavy-duty vehicle's wheelhouse. Therefore, aluminum suspension control arms technology will not always be appropriate for vehicles in the heavy-duty fleet.[618]

As a result of this reduced level of MR diversity, the CAFE Model for heavy-duty pickups and heavy-duty vans only considers two levels of MR technologies that heavy-duty manufacturers could use as pathways to compliance with CAFE standards. The magnitude of MR in percent for each of these levels is shown in as a percentage of vehicle glider weight, and curb weight for both heavy-duty pickups and heavy-duty vans (See Table 3-100).

[617] Body-in-white is a primary structure of a passenger vehicle typically made up of stamped sheet metal components and sub-assemblies that are joined through processes such as spot welding, adhesive bonding, riveting, etc. to form a rigid shell onto which all the vehicle's other systems can be mounted. The body in white also includes closure sub-assemblies such as doors, deck lids and hoods, although these parts are not primary structure. It is also referred to sometimes as a "unit body" or "monocoque." Note that the body in white is distinctly different than a chassis because it does not include any suspension components or wheels.
[618] Baskin, D.M. 2000. A Perspective on Future Automotive Chassis Component Materials. *Materials Technologies*. Vol. 15(4): at 290-95. Available at: https://www.tandfonline.com/doi/abs/10.1080/10667857.2000.11752894. (Accessed: Feb. 12, 2024).

Table 3-100: Mass Reduction Technology Level and Associated Glider and Curb Mass Reduction for HDPUVs

MR Level	Percent Glider Weight	Percent Vehicle Curb Weight (HD Pickups)	Percent Vehicle Curb Weight (HD Vans)
MR0	0.00%	0.00%	0.00%
MR1	1.4%	1.0%	1.0%
MR2	13.0%	9.23%	9.23%

Achieving higher levels of MR in heavy-duty vehicles is potentially achievable with extensive use of fiberglass or carbon fiber composite technology. However, given the larger size of components made for heavy-duty pickups and vans, a proportionately higher amount of expensive composite material would be necessary to achieve these higher MR levels. Such technology is not currently observed in the fleet.

3.4.1.3. Primary and Secondary Mass Reduction

Each of the subsystems in a vehicle presents an opportunity for weight reduction; however, some weight reduction is dependent on the weight reduction of other subsystems. Mass reduction is often characterized as either primary MR or secondary MR. Primary MR involves reducing the mass of components that can occur independent from the mass of other components. For example, reducing the mass of a hood (e.g., replacing a steel hood with an aluminum hood) or reducing the mass of a seat, are examples of primary MR because each can be implemented independently. Other components and systems that may contribute to primary MR include the vehicle body, chassis, and interior components.

When significant primary MR occurs, other components designed based on the mass of primary components may be redesigned as well. An example of a subsystem where secondary MR can be applied is the brake system. If the mass of primary components is reduced sufficiently, the resulting lighter weight vehicle could safely maintain braking performance and attributes with a lighter weight brake system. Other examples of components where secondary MR can be applied are wheels and tires.

Our MR levels implicitly assume primary and secondary MR happens in a specific order, to apply technologies in the order of cost effectiveness while ensuring that secondary MR is applied after sufficient primary MR has been applied to enable the secondary MR.

Some MR is more valuable to fuel savings than other MR. All mass on a vehicle contributes to the translating (vehicle reference frames move relative to its surroundings) mass of the vehicle. However, some mass on a vehicle is simultaneously translating and rotating (rotates relative to the reference frame of the vehicle). For example, wheels, brake rotors, and hub flanges fall into this category. This is in contrast to components like fuel tanks, windshields, rear seats, etc. that only translate with the vehicle. Weight reduction of components that are rotating and translating offer greater fuel savings. This is because when a vehicle accelerates not only must the translational inertia of the vehicle as a whole be overcome, but the rotational moment of inertia must be overcome for these components as well. This requires more energy than if they were just translating. Therefore, reducing the mass of these components provides an increased benefit.

As discussed further in Chapter 3.4.5, we developed the cost curves used in this analysis by sequencing the light-weighted components from the model year 2011 Honda Accord and model year 2014 Chevrolet Silverado studies[619,620] based on cost effectiveness. They assumed the vehicle body, chassis, interior, and other primary components were light-weighted first, followed then by light-weighting powertrain components

[619] Singh, H. 2012. Mass Reduction for Light-Duty Vehicles for Model Years 2017-2025. Final Report. DOT HS 811 666. Available at: https://static.nhtsa.gov/nhtsa/downloads/CAFE/2017-25_Final/811666.pdf. (Accessed: May 31, 2023).
[620] Singh, H. et al. 2018. Mass Reduction for Light-Duty Vehicles for Model Years 2017-2025. DOT HS 812 487. Available at: https://www.nhtsa.gov/sites/nhtsa/files/documents/13250f-peer_review_comment_resolution_document-final-112818-v3-tag.pdf. (Accessed: Feb. 12, 2024).

and other secondary systems after there is sufficient primary MR. Following the publication of these light-weighting studies, peer reviewers and manufacturers commented that many common components that are shared across all of the powertrains and vehicle models, such as drive axles, engine cradles, and radiator engine support that are considered to be non-powertrain secondary MR opportunities cannot be downsized. This is because the same components are used across many vehicles with different powertrain options to maximize economies of scale. Even though some of these components may provide opportunities for additional MR, we agree with peer reviewers and manufacturers that retaining a common design for all powertrain options avoids the proliferation of complexity to maintain economies of scale.

The cost curves based on our light-weighting studies reflect that, returning to this example, secondary MR for the brake system is only applied after there has been sufficient primary MR to allow the smaller brake system to provide safe braking performance and to maintain mechanical functionality. This allows us to estimate the cost of MR independently of the cost associated with downsized advanced engines and advanced transmissions, as the cost of downsized advanced engines and transmissions are accounted for separately in the CAFE Model. Therefore, the five MR levels included in this analysis appropriately reflect both primary and secondary MR opportunities.

3.4.2. Mass Reduction Analysis Light-Duty Fleet Assignment

To assign initial MR levels (MR0 through MR5) for light-duty vehicles in the light-duty analysis fleet, we used previously developed regression models that were used for the 2015 rulemaking analysis to estimate curb weight for each vehicle based on observable vehicle attributes. In some cases, for this analysis we used model year 2016 and 2017 analysis fleet data to update for some key models, like the aluminum-bodied Ford F-150.

To assign initial MR levels (MR0 through MR2) to the heavy-duty pickup truck and heavy-duty van fleets we developed new regression models using a hybrid of fleets spanning from 2014 to 2022 and used this new regression model to estimate curb weight for each work vehicle based on observable vehicle attributes.

To develop the curb weight regressions, we grouped vehicles into five separate body design categories: 3-box, 2-box, pickup, heavy-duty pickup, and heavy-duty van as seen in Table 3-101. A 3-box can be explained as having a box in the middle for the passenger compartment, a box in the front for the engine and a box in the rear for the luggage compartment. A 2-box has a box in front for the engine and then the passenger and luggage box are combined into a single box.

Table 3-101: Mass Reduction Body Style Sets

3-Box	2-Box	Pick-up	HD Pickup	HD Van
Coupe Sedan Convertible	Hatchback Wagon Sport Utility Minivan Van	Pick-up	Work Truck Chassis Cab	Work Van Cutaway

For this analysis, we retained the model year 2015 regressions for 3-Box and 2-Box vehicles. While many of the vehicles share the same powertrain for passenger cars and SUVs or for cars and pickup trucks, the utility and functionality of the vehicle in SUVs and pickup trucks (2-box) is different than passenger cars (3-box). The presence of additional structure for towing or higher capacity towing, rear cross member, higher capacity suspension, and other differences, enable SUVs and pickup trucks to have towing and heavier payload capability. For example, Ford uses the nearly similar displacement and HP engines in Mustang EcoBoost Coupe and in F-150 2WD XL, Regular Cab, Long Box. However, the curb weight for the pickup truck is higher than the Mustang. Directionally, this suggests that the 2-box weight per HP coefficient should be greater than the 3-box coefficient, just as it is in the regression. The coefficient for passenger cars (2-box and 3-box) and SUVs has not changed since the model year 2015 vehicle fleet analysis.

For the 2024-2026 rulemaking and this analysis, we upgraded the pickup category regression in response to comments on the 2016 Draft TAR. We estimated a new regression with EPA model year 2014 CAFE compliance data and added pick-up bed length as an independent variable. This upgrade also include addition of the largely aluminum F-150. Looking back at the model year 2014 data for the pick-up regression, the dataset did not include the all-aluminum body Ford F-150 in the calculation of the regression. The advanced F-150 in the model year 2015 pick-up regression meaningfully affected Draft TAR regression statistics because the F-150 accounted for a large portion of observations in the analysis fleet, and the F-150 included advanced weight savings technology.

We leveraged many documented variables in the light-duty analysis fleet as independent variables in the regressions. Continuous independent variables used for the light-duty regression model include footprint (wheelbase x track width) and powertrain peak power. Binary independent variables include strong HEV (yes or no), PHEV (yes or no), BEV or FCEV (yes or no), AWD (yes or no), RWD (yes or no), pick-up bed length (for the pick-up truck regression only) and convertible (yes or no). In addition, for PHEV and BEV/FCEV vehicles, the capacity of the battery pack is included in the regression as a continuous independent variable. In some body design categories, the analysis fleet does not cover the full spectrum of independent variables. For instance, in the pickup body style regression, there are no front-wheel drive vehicles in the analysis fleet, so the regression defaulted to AWD and left an independent variable for RWD.

As mentioned above, we developed a separate MR regression model to predict the weight of heavy-duty pickups. Continuous independent variables used for the heavy-duty pickups for the regression model include footprint (wheelbase x track width), towing capacity, payload capacity, bed length and engine torque. Binary independent variables include 4 rear wheels (yes or no) and AWD (yes or no).

We also developed a separate MR regression model to predict the weight of heavy-duty vans. Continuous independent variables used for the heavy-duty vans for the regression model include footprint (wheelbase x track width), towing capacity, payload capacity, and engine torque. Binary independent variables include 4 rear wheels (yes or no) and AWD (yes or no).

The regression results for 3-Box, 2-Box, Pickup trucks, HD pickup trucks, and HD vans are shown in Table 3-102, Table 3-103, Table 3-104, Table 3-105 and Table 3-106.

Table 3-102: Regression Statistics for Curb Weight (lbs.) for 3-Box Vehicles

Observations	**822**					
Adjusted R Square	0.87					
Standard Error	228.70					
Regression Statistics	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-1581.63	98.50	-16.06	0.00	-1775.00	-1388.30
Footprint (sq. ft.)	100.5	2.2	44.79	0	69.1	104.9
Power (hp)	1.22	0.1	14.85	0	1.1	1.4
Bed length (inches)	-	-	-	-	-	-
Strong HEV (1,0)	200.36	46.3	4.33	0	109.5	291.2
PHEV (1,0)	259.28	96.8	2.68	0.0075	69.3	449.2
BEV or FCEV (1,0)	602.33	215	2.8	0.0052	180.3	1024.3
Battery pack size (kWh)	-2.48	4.1	-0.6	0.5461	-10.6	5.6
AWD (1,0)	294.51	24.5	12.03	0	246.4	342.6
RWD (1,0)	117.2	23.7	4.94	0	70.6	163.8
Convertible (1,0)	273.65	25.3	10.84	0	224.1	323.2

Table 3-103: Regression Statistics for Curb Weight (lbs.) for Pick-up Vehicles

Observations	312					
Adjusted R Square	0.84					
Standard Error	206.80					
Regression Statistics	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1062.21	130.23	8.16	0.00	805.95	1318.48
Footprint (sq. ft.)	58.31	2.37	24.96	0	53.72	62.91
Power (hp)	2.5	0.21	11.79	0	2.08	2.92
Bed length (inches)	-9.57	1.14	-8.4	0	-11.81	-7.32
Strong HEV (1,0)	-	-	-	-	-	-
PHEV (1,0)	-	-	-	-	-	-
BEV or FCEV (1,0)	-	-	-	-	-	-
Battery pack size (kWh)	-	-	-	-	-	-
AWD (1,0)	260.91	23.62	11.05	0	214.43	307.38
RWD (1,0)	-	-	-	-	-	-
Convertible (1,0)	-	-	-	-	-	-

Table 3-104: Regression Statistics for Curb Weight (lbs.) for 2-Box Vehicles

Observations	584					
Adjusted R Square	0.88					
Standard Error	332.80					
Regression Statistics	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-1930.09	142.50	-13.54	0.00	-2210.00	-1650.20
Footprint (sq. ft.)	104.72	3.6	28.69	0	97.5	111.9
Power (hp)	3.09	0.2	13.42	0	2.6	3.5
Bed length (inches)	-	-	-	-	-	-
Strong HEV (1,0)	358.97	80.3	4.47	0	201.3	516.6
PHEV (1,0)	462.9	169.7	2.73	0.01	129.5	796.3
BEV or FCEV (1,0)	374.24	152.1	2.46	0.01	75.5	673
Battery pack size (kWh)	-1.32	3.7	-0.36	0.72	-8.5	5.9
AWD (1,0)	353.91	33.4	10.59	0	288.3	419.5
RWD (1,0)	208.02	54.1	3.84	0	101.7	314.3
Convertible (1,0)	-	-	-	-	-	-

Table 3-105: HD Pickup

Observations	794					
Adjusted R Square	0.76					
Standard Error	357.05					
Regression Statistics	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	5381.90	227.55	23.669	8.02E-94	4935.23	5828.57
Footprint (sq. ft.)	21.98	2.0044	10.97	3.83E26	18.05	25.92
Payload (lbs.)	-0.267	0.018	14.53	1.52E-42	0.30	-0.23
Towing Capacity (lbs.)	0.01	0.0045	2.31	0.21	0.0015	0.019
Engine Torque (ft.*lbs.)	1.33	0.087	15.17	8.81E-46	1.15	1.50
Bed length (inches)	-3.12	1.86	1.67	0.95	-6.77	0.54
Drive Configuration (RWD or 4WD)	369.37	26.98	13.69	2.00E-38	316.41	422.32
Rear Wheel Count (2 or 4)	1216.1	58.91	20.64	5.51E-76	1100.53	1331.82

Table 3-106: HD Van

Observations	307					
Adjusted R Square	0.75					
Standard Error	597.65					
Regression Statistics	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	7880.97	562.25	14.02	1.11E-34	6774.51	8987.43
Footprint (sq. ft.)	10.30	6.62	1.57	0.12	-2.73	23.334
Payload (lbs.)	-0.97	0.048	-20.19	7.43E-58	-1.07	-0.88
Towing Capacity (lbs.)	-0.024	0.023	-1.0377	0.30	-0.069	0.021
Engine Torque (ft.*lbs.)	1.60	0.69	2.32	0.021	0.24	2.95
Drive Configuration (RWD or 4WD)	-45.85	158.51	-0.29	0.77	-357.78	266.08
Rear Wheel Count (2 or 4)	1459.41	100.31	14.55	1.17E-36	1262.02	1656.81

Each of the five regressions produced outputs effective for identifying vehicles with a significant amount of MR technology in the analysis fleet. Many coefficients for independent variables provide clear insight into the average weight penalty for the utility feature.

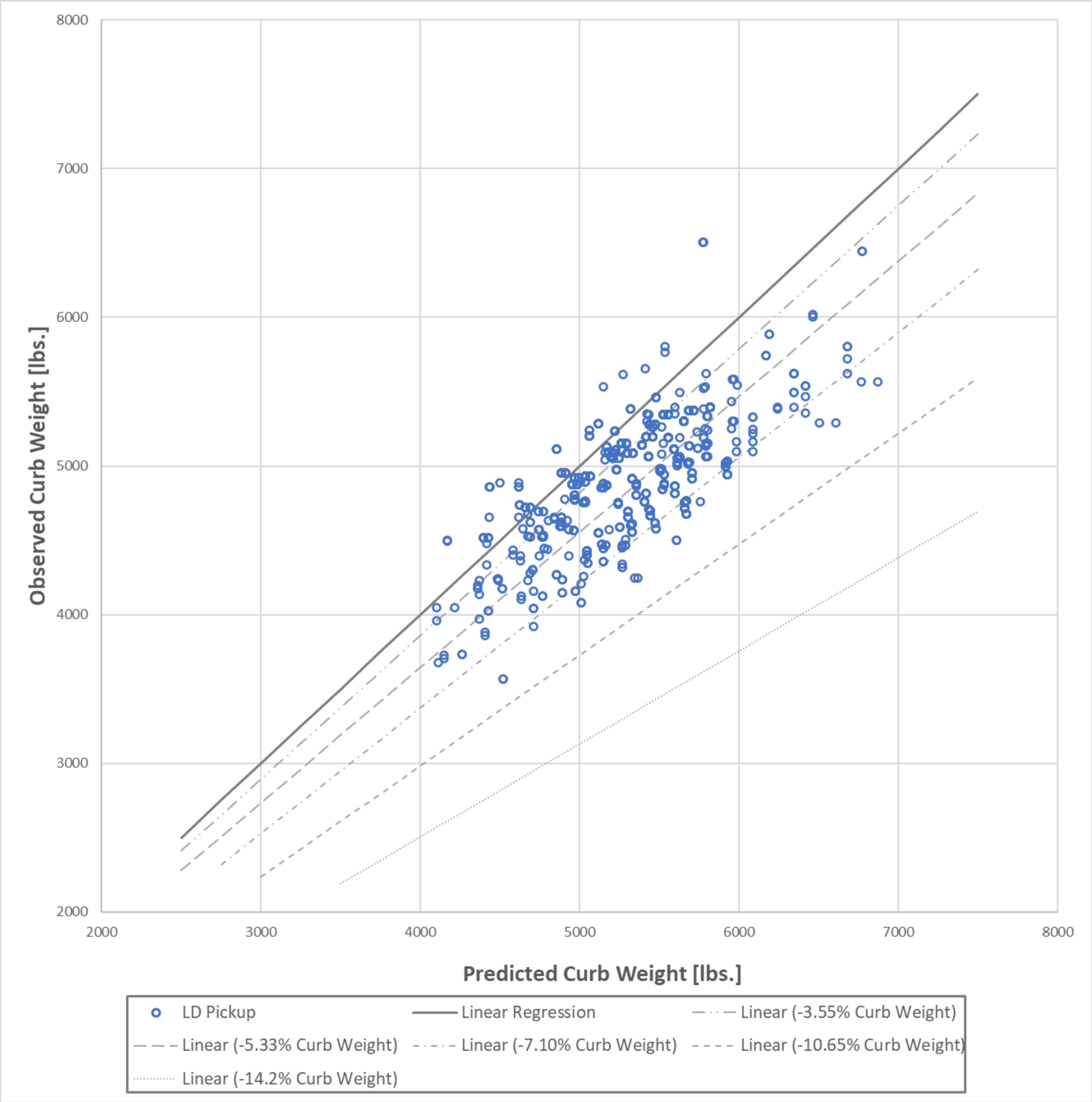
By design, no independent variable directly accounts for the degree of weight savings technology applied to the vehicle. Residuals of the regression capture weight reduction efforts and noise from other sources.

As a practical matter, we cannot conduct a tear down study and detailed cost assessment for every vehicle in every model year. However, upon review of many vehicles and their subsystems, review of fleet assignments in the 2024-2026 final rule identifies a few vehicles with MR0 or MR1 assignments where the vehicles contain some advanced weight savings technologies, yet they and their platforms still produce small residuals. Engineers from industry confirm that important factors other than glider weight savings and the independent variables considered in the regressions might factor into the use of light-weight technologies. Such factors include the desire to lower the center of gravity of a vehicle, improve the vehicle weight distribution for handling, optimize noise-vibration-and-harshness, increase torsional rigidity of the platform, offset increased vehicle content, and many other factors.[621] In addition, engineers highlight the importance of sizing shared components for the most demanding applications on the vehicle platform; optimum weight savings for one platform application may not be suitable for all platform applications. For future analysis, we will continue to look for practical ways to improve the assessment of MR content and the forecast of incremental MR costs for each vehicle.

Figure 3-34 shows results from the light-duty pickup truck regression on predicted curb weight versus actual curb weight. Points above the solid regression line represent vehicles heavier than predicted (with lower MR technology levels); points below the solid regression line represent vehicles lighter than predicted (with higher MR technology levels). The dashed lines in Figure 3-34 show the thresholds (5, 7.5, 10, 15, and 20 percent of glider weight). Again, this analysis assumes the glider weight is 71 percent of vehicle curb weight.

[621] Stoy, A. 2015. Carbon Core: 2016 BMW 7-Series Gets Carbon-Fiber Implants. Autoweek. Available at: https://www.autoweek.com/news/a1868071/carbon-core-2016-bmw-7-series-gets-carbon-fiber-implants/. (Accessed: Feb. 12, 2024).

Figure 3-34: Observed Curb Weight vs. Predicted Curb Weight for the MY 2022 Analysis Fleet for 71 Percent Glider Share for Pickup Truck



For points with actual curb weight below the predicted curb weight, we use the residual as a percent of predicted weight to get a sense for the level of current MR technology used in the vehicle. Notably, vehicles approaching -20 percent curb weight widely use advanced carbon fiber composites throughout major vehicle subsystems, and few examples exist in the model year 2022 fleet.[622]

Generally, residuals of regressions as a percent of predicted weight appropriately stratify vehicles by MR level. Most vehicles show near zero residuals or had actual curb weights close to the predicted curb weight. Few vehicles in the analysis fleet achieve the highest levels of MR. Most vehicles with the largest negative residuals demonstrably adopt advanced weight savings technologies at the most expensive end of the cost curve. There are exceptions such as with cargo vans because of their sparse interiors and consequent low weight relative to other vehicles with high luxury item content but having similarly large footprints.

[622] This evidence suggests that achieving a 20 percent curb weight reduction for a production vehicle with a baseline defined with this methodology is extremely challenging and requires advanced materials and disciplined design.

To validate the residuals, we reviewed the results for all vehicle platforms in fleet. We then compared the assigned MR values to information about the vehicles collected from websites and digital brochures to determine if the assigned MR values were reasonable. From these information sources we collected vehicle dimensional information as well as the construction materials and techniques use to make the vehicles to determine the reasonableness of the assigned MR values. We then compared that information with the designs and materials used in the MR feasibility and cost studies summarized in Chapter 3.4.5. That comparison showed consistent agreement with the technology levels derived from the regression analysis. We therefore believe the regression methodology is a technically sound approach for estimating MR levels in the analysis fleet.

Manufacturers generally apply MR technology at a vehicle platform level (i.e., using the same components across multiple vehicle models that share a common platform) to leverage economies of scale and to manage component and manufacturing complexity, so conducting the regression analysis at the platform level leads to more accurate estimates for the real-world vehicle platform MR levels. The platform approach also addresses the impact of potential weight variations that might exist for specific vehicle models, as all the individual vehicle models are aggregated into the platform group, and are effectively averaged using sales weighting, which minimizes the impact of any outlier vehicle configurations.

Table 3-107 shows the regression results to select vehicles in the light-duty passenger car fleet. Also included is Table 3-108 which shows the regression results to a few select heavy-duty pickups and heavy-duty vans.

Table 3-107: Results of the Regression Analysis for a Few Select Light-Duty Vehicles from the MY 2022 Fleet

Brand	Model	Sales Weighted Platform Mass Reduction Residual (%)	Mass Reduction Level for 71% Glider Weight
Ford	GT	-28.0	MR5
Tesla	Model S	-26.7	MR5
Lamborghini	Urus	-21.8	MR5
Bugatti	Chiron	-21.2	MR5
Hyundai	Elantra	-14.2	MR4
Lamborghini	Aventador	-13.8	MR4
Tesla	Model Y	-13.4	MR4
Mazda	MX5	-12.2	MR4
Kia	Forte	-11.8	MR4
Mercedes	AMG GT	-11.7	MR4
Hyundai	Veloster N	-11.3	MR4
Audi	R8 Coupe	-10.8	MR4
Ford	F-150	-10.5	MR3
Chevrolet	Corvette	-10.2	MR3
Jaguar	F-Pace	-10.0	MR3
Honda	Accord	-9.2	MR3
Kia	K5	-8.9	MR3
Ford	Mach-E	-8.6	MR3

Porsche	Macan	-8.3	MR3
Volkswagen	Atlas	-7.5	MR3
Toyota	Camry	-7.2	MR3
Volvo	XC90	-6.4	MR2
Nissan	Ultima	-6.2	MR2
GMC	Sierra	-6.1	MR2
Mercedes	GLB	-5.4	MR2
Land Rover	Defender	-5.4	MR2

Table 3-108: Mass Reduction Technology Levels for the HDPUV Analysis Fleet for 71% Glider Share of Curb Weight

Brand	Model	HD Van or Pickup	Sales Weighted Platform Mass Reduction Residual (%)	Mass Reduction Level for 71% Glider Weight
Ford	Transit Cargo Van	Van	-11.8	MR2
Ford	Transit Passenger Wagon	Van	-11.8	MR2
Ford	Transit Extended Cargo Van	Van	-11.8	MR2
Chevrolet	Express Cargo Van	Van	-7.71	MR1
Chevrolet	Express Passenger Van	Van	-7.71	MR1
Nissan	NV Cargo Van	Van	-7.65	MR1
Nissan	NV Passenger Van	Van	-7.65	MR1
Nissan	Titan XD	Pickup	-7.65	MR1
Mercedes-Benz	Sprinter Cargo Van	Van	-7.07	MR1
Mercedes-Benz	Sprinter Cargo Passenger	Van	-7.07	MR1
Mercedes-Benz	Sprinter Cargo and Crew	Van	-7.07	MR1

Mass Reduction Technology Levels for the hybrid Analysis Fleet for HD pickups and HD vans for 71% Glider Share of Curb Weight

3.4.3. Mass Reduction Adoption Features

Given the degree of commonality among the vehicle models built on a single platform, manufacturers do not have complete freedom to apply unique technologies to each vehicle that shares the platform. While some technologies (e.g., low rolling resistance tires) are very nearly “bolt-on” technologies, others involve substantial changes to the structure and design of the vehicle, and therefore often necessarily affect all vehicle models that share that platform. In most cases, MR technologies are applied to platform level components and therefore the same design and components are used on all vehicle models that share the platform.

Each vehicle in the analysis fleet is associated with a specific platform. Similar to the application of engine and transmission technologies, the CAFE Model defines a platform “leader” as the vehicle variant of a given platform that has the highest level of observed MR present in the analysis fleet. If there is a tie, the CAFE Model begins MR technology on the vehicle with the highest sales in model year 2022. If there remains a tie, the model begins by choosing the vehicle with the highest manufacturer suggested retail price (MSRP) in model year 2022. As the model applies technologies, it effectively levels up all variants on a platform to the highest level of MR technology on the platform. So, in the light-duty analysis, if the platform leader is already at MR3 in model year 2022, and a "follower" starts at MR0 in model year 2022, the follower will get MR3 at its next redesign (unless the leader is redesigned again before that time, and further increases the MR level associated with that platform, then the follower would receive the new MR level).

Understanding our handling of vehicles that traditionally operated on the same platform but had a mix of old and new platforms in production at the time we created the analysis fleet is important for understanding our analysis fleet MR assignments, and for understanding adoption features as well. For example, the Honda Civic and Honda CR-V are light-duty vehicles that traditionally share the same platform. In model year 2016, Honda redesigned the Civic and updated the platform to include many MR technologies. Also in model year 2016, Honda continued to build the CR-V on the previous generation platform that did not include many of the MR technologies on the model year 2016 Civic. In model year 2017, Honda launched the CR-V that incorporated changes to the Civic platform, and the Civic and CR-V again shared the same platform with common MR technologies. This analysis treats the old and new platforms separately to assign technology levels in the analysis fleets, and the CAFE Model brings vehicles on the old platform up to the level of MR technology on the new shared platform at the first available redesign year.

For nearly every type of vehicle, with the exception of the smallest sports cars, a light-duty auto manufacturer's strategy to achieve MR consistent with MR5 will require extensive use of carbon fiber technologies in the vehicles' "hang-on" components such as fenders, decklids, hoods, etc. Moreover, MR5 requires use of aluminum and advanced ultra-high strength steels. The CAFE Model applies technologies to vehicles that provide a cost-effective pathway to compliance. In some cases, the direct manufacturing cost, indirect costs, and applied learning factor do not capture all the considerations that make a technology more or less costly for manufacturers to apply in the real world. For example, there are direct labor, R&D overhead, manufacturing overhead, and amortized tooling costs that will likely be higher for carbon fiber production than current automotive steel production, due to fiber handling complexities. In addition, R&D overhead will increase because the knowledge base for composite materials in automotive applications is simply not as deep as it is for steel and aluminum. Indeed, the intrinsic anisotropic mechanical properties of composite materials compared to the isotropic properties of metals complicates the design process.

In addition, the CAFE Model does not currently enable direct accounting for the stranded capital associated with a transition away from stamped sheet metal construction to molded composite materials construction. For decades, or in some cases half-centuries, car manufacturers have invested billions of dollars in capital for equipment that supports the industry's sheet metal forming paradigm. A paradigm change to tooling and equipment developed to support molding carbon fiber panels would leave that capital stranded in equipment that would be rendered obsolete. Doing this is possible, but the financial ramifications are not currently reflected in the CAFE Model for MR5 compliance pathways.

An important factor limiting the application of carbon fiber technology to mass volume PVs is also the availability of dry carbon fibers. There is high global demand from a variety of industries for a limited supply of carbon fibers. Aerospace, military/defense, and industrial applications demand most of the carbon fiber currently produced. Today, only roughly 10 percent of the global dry fiber supply goes to the automotive industry, which translates to the global supply base only being able to support approximately 70,000 cars.[623] Unlike in the 2024-2026 analysis, there is no phase-in cap for MR5 level for the current rule. We selected an 80,000-unit threshold for MR5 technology, because it roughly reflects this volume limit plus a margin to account for reasonable expectations for expansion in the supply base. Because MR is applied at the platform level (meaning that every car of a given platform would receive the technology, not just special low volume versions of that platform), only platforms representing 80,000 vehicles or fewer are eligible to apply MR5 toward CAFE compliance.[624] Platforms representing high volume sales, like a Chevrolet Traverse, for example, where hundreds of thousands are sold per year, are therefore blocked from access to MR5

[623] Sloan, J. 2020. Carbon Fiber Suppliers Gear up for Next- Generation Growth. Last Revised: Feb. 11, 2020. Available at: https://www.compositesworld.com/articles/carbon-fiber-suppliers-gear-up-for-next-gen-growth. (Accessed: May 31, 2023).
[624] This process was implemented in the Market Data Input File by summing up all the vehicles platforms, not models, and creating a skip function for platforms that are less than 80,000 vehicles.

technology. There are no phase-in caps for light-duty MR levels MR1, MR2, MR3, or MR4, and no phase-in caps for HDPUV MR levels MR1 and MR2.

3.4.4. Mass Reduction Effectiveness

As discussed in Chapter 2.3, ANL develops databases of vehicle attributes and characteristics for each vehicle technology class that includes over 100 different attributes. Some examples from these 100 attributes include frontal area, drag coefficient, fuel tank weight, transmission housing weight, transmission clutch weight, hybrid vehicle components, and weights for components that comprise engines and electric machines, tire rolling resistance, transmission gear ratios, and final drive ratio. Argonne uses these attributes to “build” each vehicle that it uses for the effectiveness modeling and simulation.[625] Important for precisely estimating the effectiveness of different levels of MR is an accurate list of initial component weights that make up each vehicle subsystem, from which Autonomie considers potential MR opportunities.

As stated above, glider weight, or the vehicle curb weight minus the powertrain weight, is used to determine the potential opportunities for weight reduction irrespective of the type of powertrain.[626] This is because weight reduction can vary depending on the type of powertrain. For example, an 8-speed transmission may weigh more than a 6-speed transmission, and for a fixed engine displacement, a turbo charged engine along with its ancillary systems (such as pluming, heat exchanger, pop-off valve, etc.) will have a higher mass than one without a turbo charger. Autonomie simulations account for the weight of the powertrain system inherently as part of the analysis, and the powertrain mass accounting is separate from the application and accounting for MR technology levels (MR0-MR5) that are applied to the glider in the simulations. Similarly, Autonomie also accounts for battery and motor mass used in HEVs and EVs separately. This secondary MR is discussed further below.

3.4.4.1. Glider Mass and Mass Reduction

In the Autonomie simulations, MR technology is simulated as a percentage of mass removed from the specific subsystems that make up the glider, as defined for that set of simulations (including the non-powertrain secondary mass systems such as the brake system). Table 3-109 shows the average mass for each subsystem and the glider share for each of the vehicle classes for all powertrain combinations.

Table 3-109: Glider Mass Share Assessment for LD Vehicles Using A2Mac1 Data

	1	2	3	4	5	6	7	8	9	10
Vehicle Class	Avg. Body Mass [kg]	Avg. Chassis Mass [kg]	Avg. Interior Mass [kg]	Avg. Brakes Mass [kg]	Avg. Steering Mass [kg]	Avg. Electrical Accessory Mass [kg]	Avg. Wheels Mass [kg]	Avg. Glider Mass (Sum of 1 to 7) [kg]	Avg. Curb Weight [kg]	% Glider Share
Compact Non-Performance	525.00	160.00	150.00	50.13	20.00	30.26	42.00	977.40	1338.71	73.01 %
Compact Performance	525.00	160.00	200.00	55.12	22.00	35.25	45.00	1042.37	1455.85	71.60 %
Midsize Non-Performance	650.00	200.00	175.00	60.13	25.00	30.26	54.00	1194.40	1611.24	74.13 %
Midsize Performance	650.00	200.00	200.00	65.12	28.00	40.25	57.00	1240.37	1734.89	71.50 %

[625] CAFE Analysis Autonomie Documentation chapter titled “Autonomie Simulation Process.”
[626] Depending on the powertrain combination, the total curb weight of the vehicle includes glider, engine, transmission and/or battery pack and motor(s).

Small SUV Non-Performance	650.00	200.00	180.00	60.13	25.00	30.26	60.00	1205.40	1651.09	73.01 %
Small SUV Performance	650.00	200.00	220.00	75.12	28.00	40.25	66.00	1279.37	1792.46	71.38 %
Midsize SUV Non-Performance	650.00	200.00	200.00	70.13	30.00	30.26	66.00	1246.40	1754.57	71.04 %
Midsize SUV Performance	750.00	225.00	240.00	75.12	30.00	50.25	78.00	1448.37	2045.42	70.81 %
Pickup Non-Performance	650.00	300.00	160.00	90.12	30.00	80.47	78.00	1388.58	2020.13	68.74 %
Pickup Performance	800.00	350.00	200.00	95.11	30.00	100.44	90.00	1665.55	2345.18	71.02 %
Average										71.62 %

For the purposes of determining a reasonable percentage for the glider, we consulted with Argonne to examine glider weight data available in the A2Mac1 database.[627] The A2Mac1 database tool is widely used by industry and academia to determine the bill of materials and mass of each component in the vehicle system.[628] We analyzed a total of 147 model year 2014 to 2016 vehicles, covering 35 vehicle brands with different powertrain options representing a wide array of vehicle classes, to determine the percentage of the vehicle comprised by the glider.[629]

We also considered that the NHTSA passenger car and light truck light-weighting studies examine MR in the body, chassis, interior, brakes, steering, electrical accessory, and wheels subsystems and have developed costs for light-weighted components in those subsystems. As a result, we believe that it is appropriate to include all of those subsystems as available for MR as part of the glider. Therefore, all of these systems are included for the analysis of glider weight using the A2Mac1 database.

These data are also compared with the glider weight measured in the NHTSA model year 2014 Chevrolet Silverado light-weighting study[630] (discussed further below), and the glider weight data range is similar to the analysis results. Accordingly, we assumed that the glider weight comprised 71 percent of the vehicle curb weight. This assumption was used for both light-duty vehicles and HDPUVs. We determined that this was reasonable for HDPUVs based on the review of MR technologies in the 2010 heavy-duty NAS study.[631]

3.4.4.2. Powertrain Mass Reduction

We account for all MR due to powertrain improvements separately from glider MR. Autonomie considers several components for powertrain MR, including engine downsizing, and, fuel tank, exhaust systems, and cooling system light-weighting.[632]

With regard to the light-duty vehicle fleet, the 2015 NAS report suggested an engine downsizing opportunity exists when the glider mass is light-weighted by at least 10 percent. The 2015 NAS report also suggested that 10 percent light-weighting of the glider mass alone would boost fuel economy by 3 percent and any engine downsizing following the 10 percent glider MR would provide an additional 3 percent increase in fuel

[627] A2Mac1: Automotive Benchmarking. (Proprietary data). Retrieved from https://portal.a2mac1.com/. (Accessed: Feb. 12, 2024).
[628] Bill of material (BOM) is a list of the raw materials, sub-assemblies, parts, and quantities needed to manufacture an end-product.
[629] Docket No. NHTSA-2018-0067-1490.
[630] Singh, H. et al. 2018. Mass Reduction for Light-Duty Vehicles for Model Years 2017-2025. DOT HS 812 487. Available at: https://www.nhtsa.gov/sites/nhtsa.gov/files/documents/13250f-peer_review_comment_resolution_document-final-112818-v3-tag.pdf. (Accessed: Feb. 12, 2024).
[631] National Research Council. 2010. Technologies and Approaches to Reducing the Fuel Consumption of Medium- and Heavy-Duty Vehicles. *The National Academies Press:* Washington, D.C. at 120-21. Available at: https://doi.org/10.17226/12845. (Accessed:Feb. 12, 2024).
[632] Although we do not acount for MR in transmissions, we do reflect design improvements as part of MR when going from, for example, an older AT6 to a newer AT8 that has similar if not lower mass.

economy.[633] The NHTSA light-weighting studies applied engine downsizing (for some vehicle types but not all) when the glider weight was reduced by 10 percent. Accordingly, the analysis limits engine resizing to several specific incremental technology steps; important for this discussion, engines in the analysis are only resized when MR of 10 percent or greater is applied to the glider mass, or when one powertrain architecture replaces another architecture.

For the HDPUV analysis, we do not allow engine downsizing at any MR level. This is because HDPUV designs are sized with the maximum GVWR and GCWR in mind, as discussed earlier in this chapter. We are objectively controlling the vehicles' utility and performance by this method in Autonomie. For example, if more MR technology is applied to a heavy-duty van, the payload capacity increases while maintaining the same maximum GVWR and GCWR.[634] The lower laden weight enables these vehicles to improve fuel efficiency by increased capacity.

Argonne performed a regression analysis of engine peak power versus weight for a previous analysis based on attribute data taken from the A2Mac1 benchmarking database,[635] to account for the difference in weight for different engine types for both light-duty vehicles and HDPUVs. For example, to account for weight of different engine sizes like 4-cylinder versus 8-cylinder, Argonne developed a relationship curve between peak power and engine weight based on the A2Mac1 benchmarking data. For this analysis, we use this relationship to estimate mass for all engine types regardless of technology type (e.g., VVL and direct injection). We apply weight associated with changes in engine technology by using this linear relationship between engine power and engine weight from the A2Mac1 benchmarking database. When a vehicle in the analysis fleet with an 8-cylinder engine adopts a more fuel-efficient 6-cylinder engine, the total vehicle weight reflects the updated engine weight with two less cylinders based on the peak power versus engine weight relationship.

When Autonomie selects a powertrain combination for a light-weighted glider, the engine and transmission are selected such that there is no degradation in the performance of the vehicle relative to the initial vehicle. The resulting curb weight is a combination of the light-weighted glider with the resized and potentially new engine and transmission. This approach is slightly different for HDPUVs, where the resizing occurs with maximum GVWR and GCWR instead of curb weight. This methodology also helps in accurately accounting for the cost of the glider and cost of the engine and transmission in the CAFE Model.

Secondary MR is possible from some of the components in the glider after MR has been incorporated in primary subsystems (body, chassis, and interior). Similarly, engine downsizing and powertrain secondary MR is possible after certain level of MR is incorporated in the glider. For the analysis, we include both primary MR, and when there is sufficient primary MR, additional secondary MR. The Autonomie simulations account for the aggregate of both primary and secondary glider MR, and separately for powertrain mass.

Note that secondary MR is integrated into the MR cost curves. Specifically, the NHTSA studies, upon which the cost curves depend, first generated costs for light-weighting the vehicle body, chassis, interior, and other primary components, and then calculated costs for light-weighting secondary components. Accordingly, the cost curves reflect that, for example, secondary MR for the brake system is only applied after there has been sufficient primary MR to allow the smaller brake system to provide safe braking performance and to maintain mechanical functionality.

We enhanced the accuracy of estimated engine weights by creating multiple curves to represent separately naturally aspirated engine designs and turbocharged engine designs for gasoline fuels and diesel fuels.[636] This achieves two benefits. First, small naturally aspirated 4-cylinder engines that adopt turbocharging technology reflect the increased weight of associated components like ducting, clamps, the turbocharger itself, a charged air cooler, wiring, fasteners, and a modified exhaust manifold. Second, larger cylinder count engines like naturally aspirated 8-cylinder and 6-cylinder engines that adopt turbocharging and downsized technologies would have lower weight due to having fewer engine cylinders. For this analysis, a naturally

[633] National Research Council. 2015. Cost, Effectiveness, and Deployment of Fuel Economy Technologies for Light-Duty Vehicles. *The National Academies Press:* Washington, D.C. Available at: https://doi.org/10.17226/21744. (Accessed: Feb. 12, 2024).
[634] National Research Council. 2010. Technologies and Approaches to Reducing the Fuel Consumption of Medium- and Heavy-Duty Vehicles. *The National Academies Press*: Washington, D.C. at 116. Available at: https://doi.org/10.17226/12845. (Accessed: Feb. 12, 2024).
[635] CAFE Analysis Autonomie Documentation chapter titled "Engine Weight Determination.
[636] Chapter "Vehicle Component Weight Selection" of the CAFE Analysis Autonomie Documentation.

aspirated 8-cylinder engine that adopts turbocharging technology and is downsized to a 6-cylinder turbocharged engine appropriately reflects the added weight of the turbocharging components, and the lower weight of fewer cylinders.

We believe it is reasonable to allow engine resizing for light-duty vehicles upon adoption of 7.1, 10.7, and 14.2 (see Table 3-97) percent curb weight reduction, but not at 3.6 and 5.3 percent.[637] Resizing is also allowed upon changes in powertrain type or the inheritance of a powertrain from another vehicle in the same platform. The increments of these higher levels of MR, or complete powertrain changes, more appropriately match the typical engine displacement increments that are available in a manufacturer's engine portfolio.

3.4.4.3. The Summary of Mass Reduction Technology Effectiveness

The range of effectiveness values for the MR technologies for the 10 light-duty vehicle technology classes are shown in and Figure 3-35 and Figure 3-36 for the unconstrained application of technology scenario and for the standard settings scenarios (which necessarily limit technology application) respectively. Similarly, the range of effectiveness for the MR technologies for the unconstrained application of technology for the four HDPUV classes are shown in Figure 3-37. As discussed earlier, Autonomie simulates all possible combinations of technologies for fuel consumption improvements. For a few technology combinations, MR has minimal impact on effectiveness on the regulatory 2-cycle test. For example, if an engine is operating in an efficient region of the fuel map on the 2-cycle test further reduction of mass may have smaller improvement on the regulatory cycles. As such, Figure 3-35, Figure 3-36, and Figure 3-37 show the range of improvements based on the full range of other technology combinations for the light-duty and HDPUV fleets.

[637] These curb weight reductions equate to the following levels of MR as defined in the analysis: MR3, MR4, and MR5, but not MR1 and MR2; additional discussion of engine resizing for MR can be found in Chapter 2.3.

Figure 3-35: LD Mass Reduction Technology Effectiveness Values for All Vehicle Technology Classes (Unconstrained)

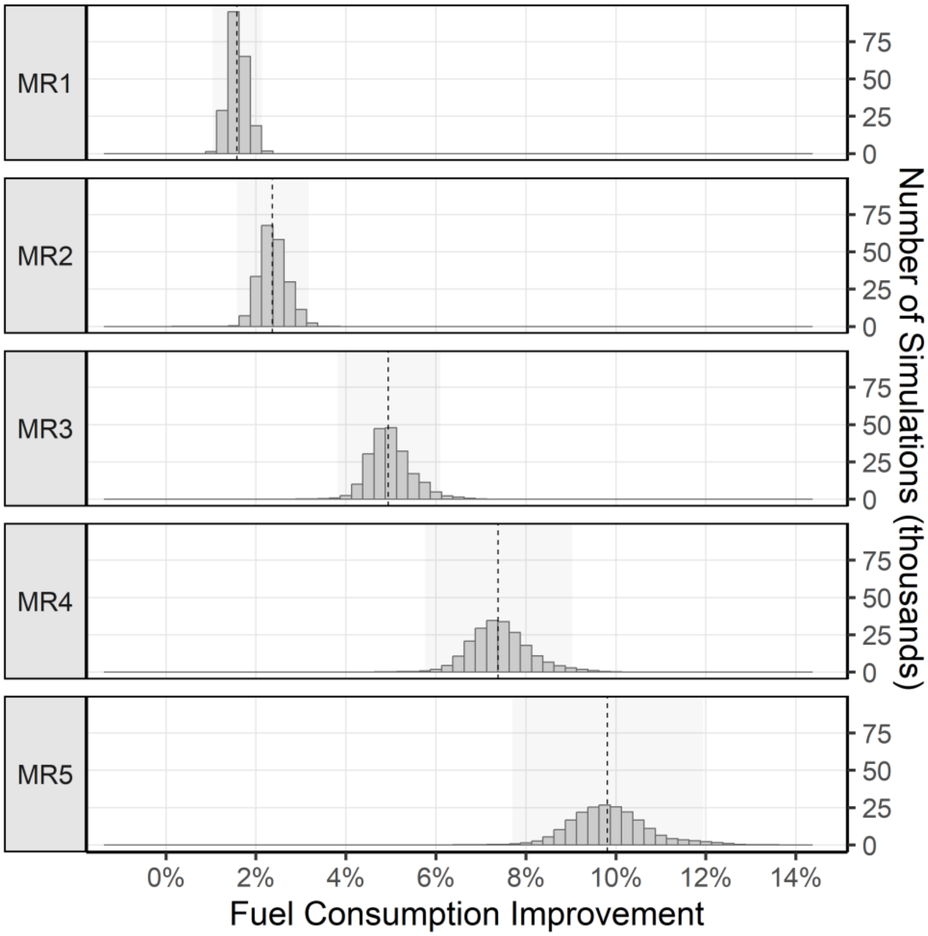


Figure 3-36: LD Mass Reduction Technology Effectiveness Values for All Vehicle Technology Classes (Standard Setting)

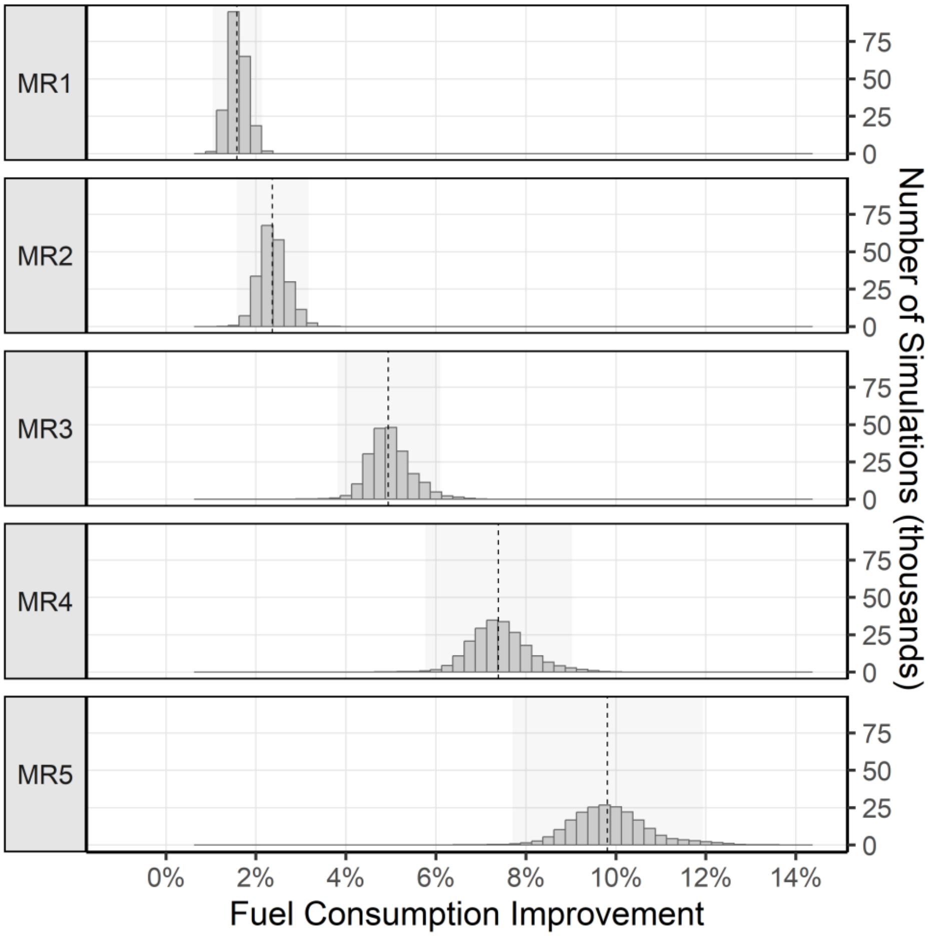
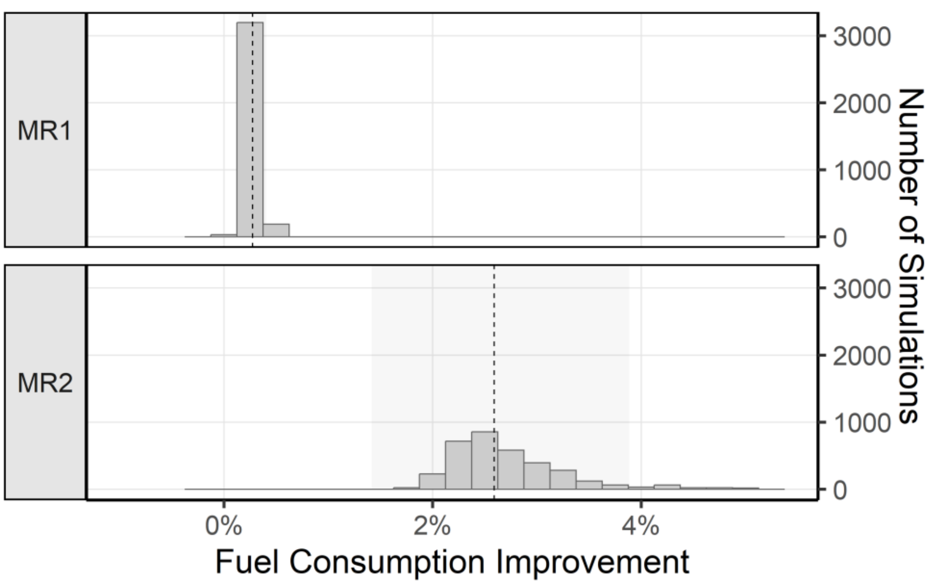


Figure 3-37: HDPUV Mass Reduction Technology Effectiveness Values for All Technology Classes



3.4.5. Mass Reduction Costs

The CAFE Model uses cost information collected from various studies and industry data to determine which pathways to compliance are most financially efficient, accounting for several real-world factors.[638] This cost information does not come in the form of a single cost point for a given piece of technology. Rather, it comes in the form of a cost curve that shows how the cost of a technology is estimated to change with time. This approach better reflects reality because technology tends to become less expensive with time as people and companies learn how to produce it more efficiently. Including the estimated cost over time of a technology also allows the CAFE Model to determine cost effective pathways to compliance that may shift based on the changes in cost effectiveness over time.

Several MR studies have used either a mid-size passenger car or a full-size pickup truck as an exemplar vehicle to demonstrate the technical and cost feasibility of MR.[639,640] While the findings of these studies may not apply directly to different vehicle classes, the cost estimates derived for the MR technologies identified in these studies can be useful for formulating general estimates of costs. As discussed further below, the MR cost curves developed for this analysis are based on two previous NHTSA light-weighting studies and were updated based on more recent studies to better account for the cost of carbon fiber needed for the highest levels of MR technology. The two NHTSA-sponsored studies used for MR1 through MR4 costs include the teardown of a model year 2011 Honda Accord and a model year 2014 Chevrolet Silverado pickup truck, and the carbon fiber costs for MR5 were updated based on the 2021 NAS report.[641]

Both NHTSA-sponsored teardown studies are structured to derive the estimated cost for each of the MR technology levels. We rely on the results of those studies because they consider an extensive range of material types, material gauge, and component redesign while taking into account real world constraints such as manufacturing and assembly methods and complexity, platform-sharing, and maintaining vehicle utility, functionality and attributes, including safety, performance, payload capacity, towing capacity, handling, NVH, and other characteristics. In addition, we believe that the vehicles and MR technologies assessed in the NHTSA-sponsored studies are still reasonably representative of the technologies that may be applied to vehicles in the model year 2022 analysis fleet to achieve up to MR4 level MR in the rulemaking timeframe. We adjust the cost estimates derived from the two NHTSA light-weighting studies to reflect the assumption that a vehicle's glider weight consists of 71 percent of the vehicle's curb weight, and MR as it pertains to achieving MR0-MR5 levels would only come from the glider.

After reviewing other agency, CARB, ICCT and industry studies,[642] we believe that the NHTSA-sponsored studies account for significant factors that are important to include on our analysis. The other studies often do not prioritize factors in an order that we agree with, make assumptions about key vehicle systems that we believe to be inaccurate, and/or apply secondary MR before adequate primary MR is applied to enable the secondary MR, resulting in unrealistically low costs. Regarding safety, we use studies that consider small overlap impact tests conducted by the Insurance Institute for Highway Safety (IIHS) and not all studies take that test into account. In addition to considering platform-sharing constraints, the NHTSA pickup truck study accounts for vehicle functional performance for attributes including towing, noise and vibration, and gradeability. This is consistent with the objective to maintain vehicle functionality throughout technology application in the analysis.

Note that the MR studies provide MR costs for the glider, and this enables more direct use of cost curve data from the studies in the CAFE Model. This change also allows Autonomie to account for powertrain mass, which enables the CAFE Model to account more accurately for the unique mass of each of the powertrains

[638] To get a better understanding of how the CAFE model finds the most cost and performance effective pathways see Chapter 2.3 (Tech Effectiveness Values) and Chapter 2.6 (Technology Applicability Rules) of this document.
[639] Singh, H. 2012. Mass Reduction for Light-Duty Vehicles for Model Years 2017-2025. Final Report. DOT HS 811 666. Available at: https://static.nhtsa.gov/nhtsa/downloads/CAFE/2017-25_Final/811666.pdf. (Accessed: Feb. 12, 2024).
[640] Singh, H. et al. 2018. Mass Reduction for Light-Duty Vehicles for Model Years 2017-2025. DOT HS 812 487. Available at: https://www.nhtsa.gov/sites/nhtsa.gov/files/documents/13250f-peer_review_comment_resolution_document-final-112818-v3-tag.pdf. (Accessed: Feb. 12, 2024).
[641] This analysis applied the cost estimates per pound derived from passenger cars to all passenger car segments, and the cost estimates per pound derived from full-size pickup trucks to all light-duty truck and SUV segments. The cost estimates per pound for carbon fiber (MR5) were the same for all segments.
[642] As for past rulemaking analyses, studies by EPA, CARB, Transport Canada, the American Iron and Steel Institute (AISI), the Aluminum Association, and the American Chemistry Council were all reviewed for potential incorporation into the analysis.

that are available in each vehicle model. The cost of the engine, transmission, and electrification are accounted for separately from the glider in the CAFE Model.

We calculated the costs of MR as an average cost per pound over the base level (MR0) for the vehicle's glider weight. While the definitions of glider may vary from study to study, we reference the same dollar per pound of curb weight to develop costs for different glider definitions. In translating these values, we took care to track units ($/kg vs. $/lb.) and the reference for percentage improvements (glider vs. curb weight).

We calculated the cost of MR on a glider weight basis so that the weight of each powertrain configuration could be directly and separately accounted for. This approach provides the true cost of MR without conflating the mass change and costs associated with downsizing a powertrain or adding additional advanced powertrain technologies. Hence, the MR costs in this rule reflect the cost of MR in the glider and do not include the MR associated with engine downsizing. We accounted for MR and costs associated with engine downsizing separately.

A second reason for using glider share instead of curb weight is that it affects the absolute amount of curb weight reduction applied, and therefore cost per pound for the MR changes with the change in the glider share. The cost for removing 20 percent of the glider weight when the glider represents 75 percent of a vehicle's curb weight is not the same as the cost for removing 20 percent of the glider weight when the glider represents 50 percent of the vehicle's curb weight. For example, the glider share of 79 percent of a 3,000-pound curb weight vehicle is 2,370 lbs., while the glider share of 50 percent of a 3,000-pound curb weight vehicle is 1,500 lbs., and the glider share of 71 percent of a 3,000-pound curb weight vehicle is 2,130 lbs. The mass change associated with 20 percent MR is 474 lbs. for 79 percent glider share (= [3,000 lbs. x 79% x 20%]), 300 lbs. for 50 percent glider share (= [3,000 lbs. x 50% x 20%]), and 426 lbs. for 71 percent glider share (= [3,000 lbs. x 71% x 20%]). The MR cost studies that we relied on to develop MR costs for this analysis show that the cost for MR varies with the amount of MR. Therefore, for a fixed glider MR percentage, different glider share assumptions will have different costs.

Note that the cost curves used for calculating the cost of MR for heavy-duty pickup trucks and heavy-duty vans are based on the cost curves used for the light-duty fleet. The light-duty and heavy-duty curves are parallel, but the heavy-duty MR2 curve is shifted to account for the fact that the MR2 level for the heavy-duty fleet represents a different percent MRs compared to the light-duty fleet. We used linear interpolation to determine how far to shift each curve. In the case of MR1 for the heavy-duty analysis, the costs are the same for light-duty and heavy-duty. In the case of MR2 for heavy-duty, the curve is shifted to a higher cost level by roughly a factor of 20. This is because MR2 for the heavy-duty fleet is roughly the MR4 and MR5 levels selected for the light-duty fleet.

3.4.5.1. Updates to MR5 Costs Based on Carbon Fiber Studies

As discussed above, achieving the highest levels of MR often necessitates use of advanced materials like higher grades of aluminum, magnesium, or carbon fiber. For the 2024-2026 final rule, DOT provided a survey of information available regarding carbon fiber costs compared to the costs DOT obtained from NHTSA's two previously mentioned teardown studies. In the model year 2011 Honda Accord MR study, the estimated cost of carbon fiber was $6.91/lbs. ($15.37/kg) and the cost of carbon fiber used in the model year 2014 Chevy Silverado MR study was $6.98/kg ($15.50/kg). The $6.98/kg ($15.50 estimate closely matched the cost estimates from a BMW i3 teardown analysis,[643] the cost figures provided by ORNL for a study from the Institute for Advanced Composites Manufacturing Innovation (IACMI),[644] and from a Ducker Worldwide presentation at the Center for Automotive Research Management Briefing Seminar.[645]

For this analysis, we relied on the cost estimates for carbon fiber construction that the National Academies detailed in the 2021 Assessment of Technologies for Improving Fuel Economy of Light-Duty Vehicles – Phase

[643] Munro and Associates Inc. 2015. BMW i3 Cost Analysis Zone 1.
[644] Institute for Advanced Composites Manufacturing Innovation. IACMI Baseline Cost and Energy Metrics. 2017. Available at https://iacmi.org/wp-content/uploads/2017/12/IACMI-Baseline-Cost-and-Energy-Metrics-March-2017.pdf. (Accessed: May 31, 2023).
[645] Ducker Worldwide LLC. 2016. The Road Ahead – Automotive Materials. Available at: https://societyofautomotiveanalysts.wildapricot.org/resources/Pictures/SAA%20Sumit%20slides%20for%20Abey%20Abraham%20of%20Ducker.pdf. (Accessed: May 31, 2023).

3.[646] The study indicates that the sum of direct materials costs plus manufacturing costs for carbon fiber composite automotive components is $25.97/lbs.($57.71/kg) in high volume production. In order to use this cost in the CAFE Model it must be put in terms of dollars per pound saved. Using an average vehicle curb weight of 4000 lbs., a 71% glider share and the percent mass savings associated with MR5, it is possible to calculate the number of pounds to be removed to attain MR5. Also taken from the NAS study is the claim that carbon fiber substitution for steel in an automotive component results in a 50% MR. Combining all this together, carbon fiber technology offers weight savings at $24.60 per pound saved. This dollar per pound savings figure must also be converted to a RPE to account for various commercial costs associated with all automotive components. This is accomplished by multiplying $24.60 by the factor 1.5. This brings the cost per pound saved for using carbon fiber to $36.90 per pound saved.[647] The analysis uses this cost for achieving MR5.

Table 3-110 and Table 3-111 show the cost values used in the CAFE Model for the light-duty fleet with MR1-4 costs based on the cost curves developed from the model year 2011 Honda Accord and model year 2014 Chevrolet Silverado studies, and the updated MR5 values that account for the updated carbon fiber costs from the 2021 NAS report. Table 3-112 shows the cost values used in the CAFE Model for the heavy-duty truck and heavy-duty van fleet and are based on values used in the light-duty fleet but were adjusted for the different MR percentages necessary to reach the three different MR levels for the heavy-duty vehicle fleets. All tables assume a 71% glider share.

Table 3-110: Mass Reduction DMCs (2021$) in CAFE Model for Small Car, Small Car Performance, Medium Car, Medium Car Performance, Small SUV, Small SUV Performance

	Percentage Reduction in Glider Weight	Percentage Reduction in Curb Weight	Cost of Mass Reduction (2021$/lbs)
MR0	0.00%	0.00%	$0.00
MR1	5.00%	3.55%	$0.30
MR2	7.50%	5.33%	$0.80
MR3	10.00%	7.10%	$1.32
MR4	15.00%	10.65%	$1.65
MR5	20.00%	14.20%	$26.46

Table 3-111: Mass Reduction DMCs (2021$) for in CAFE Model for Medium SUV, Medium SUV Performance, Pickup, Pickup HT

	Percentage Reduction in Glider Weight	Percentage Reduction in Curb Weight	Cost of Mass Reduction (2021$/lbs)
MR0	0%	0.00%	$0.00
MR1	5.00%	3.55%	$0.30
MR2	7.50%	5.33%	$0.80
MR3	10.00%	7.10%	$1.32
MR4	15.00%	10.65%	$1.65
MR5	20.00%	14.20%	$26.46

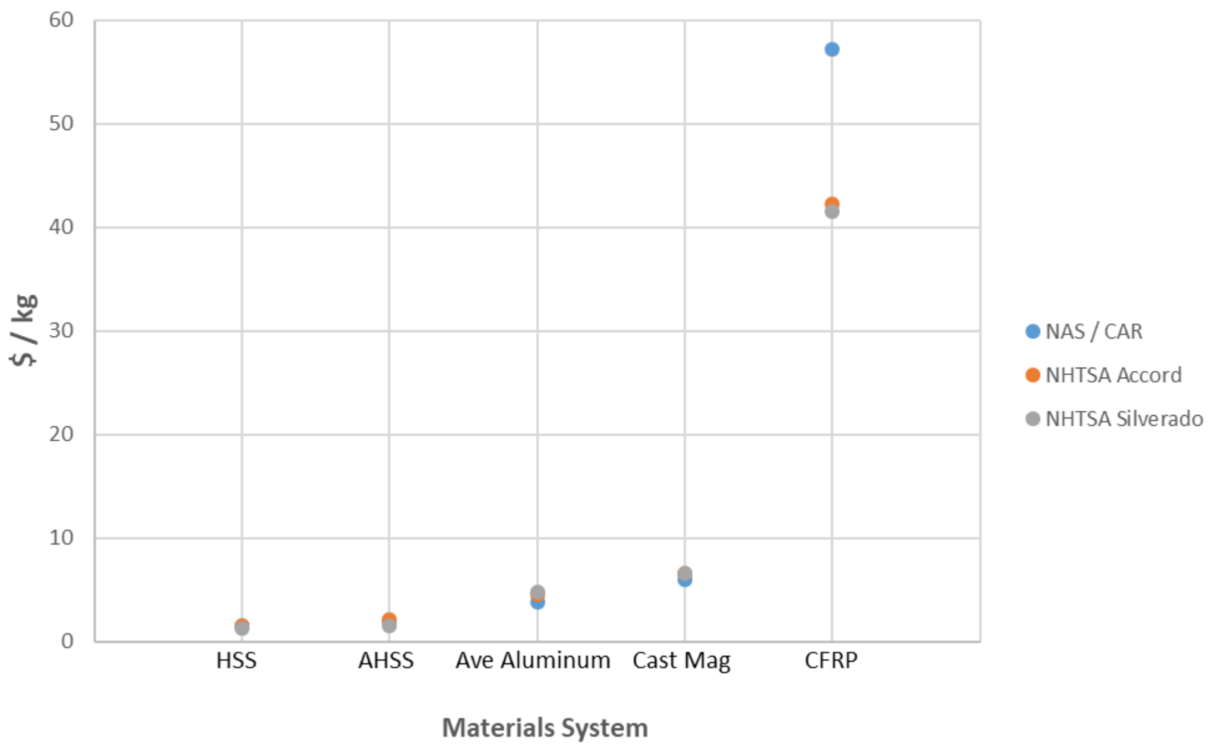
[646] 2021 NAS report, at 7-242-3.
[647] See MR5 CFRP Cost Increase Calculator.xlsx which can be found in the rulemaking docket by filtering for Supporting & Related Materials.

Table 3-112: Mass Reduction DMCs (2021$) for in CAFE Model for HDPUVs

	Percentage Reduction in Glider Weight	Percentage Reduction in Curb Weight	Cost of Mass Reduction (2021$/lbs)
MR0	0%	0.00%	$0.00
MR1	1.4%	1.0%	$0.30
MR2	13.0%	9.23%	$18.07

There is a dramatic increase in cost going from MR4 to MR5 for all classes of vehicles. However, while the increase in cost going from MR4 to MR5 is dramatic, the model year 2011 Honda Accord study, the model year 2014 Chevrolet Silverado study, and the 2021 NAS report all included a steep increase to achieve the highest levels of MR technology, as seen in Table 3-110 and Table 3-111. Figure 3-38 shows the cost per kilogram for various materials used for MR from 2021 NAS, the NHTSA Accord study, and the NHTSA Silverado study. Again, based on studies such as the NHTSA Accord and Silverado studies, enough MR to reach MR5 will require a majority of secondary structure and possible some small portion of the primary structure, such as the bumper beams, be made from carbon fiber. The increase in cost in going from MR4 to MR5 can be justified by considering the dollar amount to purchase a pound of fully laminated and manufactured CFRP compared to the dollar amount to purchase a pound of AL, magnesium or steel as shown in Figure 3-38.

Figure 3-38: Cost per Kilogram Including Manufacturing for Various Materials (HSS = high strength steel, AHSS = advanced high strength steel, CFRP = carbon fiber reinforced plastic) Used for Mass Reduction from NAS,[648] the NHTSA Accord Study,[649] and the NHTSA Silverado[650]



[648] 2021 NAS report, at 7-242-3.
[649] DOT HS 811 666, at 145, Figure 138.
[650] DOT HS 812 487, at 102, Figure 113.

3.5. Aerodynamics

The energy required to overcome aerodynamic drag accounts for a significant portion of a vehicle's energy consumption and can become the dominant road load at high speeds. A breakdown of the power needed to propel a vehicle down the road shows a cubic increase in aerodynamic drag forces as speed increases.[651] For example, by doubling the velocity the vehicle requires eight times the power to overcome the aerodynamic drag compared to the base velocity. Reducing aerodynamic drag is, therefore, an effective way to reduce fuel consumption.

Aerodynamic drag is characterized as proportional to the frontal area (A) of the vehicle using a factor called the coefficient of drag (C_d). The coefficient of drag (C_d) is a dimensionless value that essentially represents the aerodynamic efficiency of the vehicle shape. The frontal area (A) is the cross-sectional area of the vehicle as viewed from the front. It acts with the coefficient of drag as a sort of scaling factor, representing the relative size of the vehicle shape that the coefficient of drag describes. Aerodynamic drag of a vehicles is often expressed as the product of the two values, C_dA, which is also known as the drag area of a vehicle. The force imposed by aerodynamic drag increases with the square of vehicle velocity, accounting for the largest contribution to road loads at higher speeds.[652]

Manufacturers can reduce aerodynamic drag either by reducing the drag coefficient or reducing vehicle frontal area, which can be achieved by passive or active aerodynamic technologies. Passive aerodynamics refers to aerodynamic attributes that are inherent to the shape and size of the vehicle. Passive attributes can include the shape of the hood, the angle of the windscreen, or even overall vehicle ride height. Active aerodynamics refers to technologies that variably deploy in response to driving conditions. Example of active aerodynamic technologies are grille shutters, active air dams, and active ride height adjustment. Manufacturers may employ both passive and active aerodynamic technologies to improve aerodynamic drag values.

Major improvements to aerodynamic performance occur during a vehicle redesign cycle when the manufacturer can make significant changes to the shape and size of the vehicle. Manufacturers may also make incremental improvements during a mid-cycle vehicle refresh using restyled exterior components and add-on devices, including, for example, restyled front and rear fascia, modified front air dams and rear valances, the addition of rear deck lips and underbody panels, and low-drag exterior mirrors. While manufacturers may nudge the frontal area of the vehicle during redesigns, large changes in frontal area are typically not possible without impacting the utility and interior space of the vehicle. Similarly, manufacturers may improve C_d by changing the frontal shape of the vehicle or lowering the height of the vehicle, among other approaches, but the shapes of certain body styles and airflow needs for cooling often limit C_d improvements.

The following subchapters discuss the CAFE Model's aerodynamic technology pathway and how we assign aerodynamic technology levels to vehicles in the analysis fleets, adoption features applicable to the aerodynamic technology levels, the Autonomie simulations' estimates of effectiveness improvements from aerodynamic technologies, and the costs for adding that aerodynamic technology.

3.5.1. Aerodynamic Technologies

For the light-duty analysis, we used four levels of aerodynamic improvements in the CAFE Model. Each level associates with 5, 10, 15, or 20 percent aerodynamic drag improvement values over a baseline computed for each vehicle body style. These levels, or bins, respectively correspond to the level of aerodynamic drag reduction over the baseline, e.g., "AERO5" corresponds to the 5 percent aerodynamic drag improvement value over the baseline, and so on. Technology pathway logic for levels of aerodynamic improvement consists of a linear progression, with each level superseding all previous levels, Figure 3-39.[653] For the

[651] Butcher, et al. 2000. Optimizing the University of Wisconsin's Parallel Hybrid-Electric Aluminum Intensive Vehicle. SAE 2000-01-0593. Available at: https://www.sae.org/publications/technical-papers/content/2000-01-0593/. (Accessed: Feb. 12, 2024).
[652] Pannone, G. 2015. Technical Analysis of Vehicle Load Reduction Potential for Advanced Clean Cars. Final Report. Apr. 2015. Available at: https://ww2.arb.ca.gov/sites/default/files/2020-04/13_313_ac.pdf. (Accessed: Feb. 12, 2024). The graph on page 20 shows how at higher speeds the aerodyanmic force becomes the dominant load force.
[653] CAFE Model Documentation.

HDPUVs, we only use two levels of aerodynamic improvements, associated with 10 percent (AERO10) and 20 percent (AERO20) aerodynamic drag improvement over the baseline values, Figure 3-37.

While the four levels of aerodynamic improvements are technology-agnostic, we provide a pathway to compliance for each level, based on aerodynamic data from a National Research Council (NRC) of Canada-sponsored wind tunnel testing program. The program included an extensive review of production vehicles utilizing these technologies, and industry comments.[654,655] This is intended to show potential ways that manufacturers could achieve each aerodynamic improvement level; however, manufacturers may implement different combinations of aerodynamic technologies to achieve improvement over their baseline vehicles. Table 3-113 shows the aerodynamic technologies that a manufacturer could use to achieve 5, 10, 15, and 20 percent improvements in passenger cars and SUVs. Table 3-113 shows the aerodynamic technologies that a manufacturer could use to achieve 5, 10, and 15 percent improvements in pickup trucks.

As discussed further in Chapter 3.5.4, we restrict the model from applying AERO20 to pickup trucks, which is why there is no pathway to AERO20 shown in Table 3-114. While a manufacturer could apply some aerodynamic improvement technologies across vehicle classes, like active grille shutters (used in the 2015 Chevrolet Colorado),[656] we believe that there are limitations that make it infeasible for vehicles with some body styles to achieve a 20 percent reduction in the coefficient of drag from their baseline. Again, this technology path is an example of how a manufacturer could reach each AERO level, but they would not necessarily be required to use the technologies.

Table 3-113: Combinations of Technologies That Could Achieve Aerodynamic Improvements Used in the Current Analyses for Passenger Cars and SUVs

Aero Improvement Level	Components	Effectiveness (%)
AERO5	Front Styling	2.0%
	Roof Line raised at forward of B-pillar	0.5%
	Faster A pillar rake angle	0.5%
	Shorter C pillar	1.0%
	Low drag wheels	1.0%
AERO10	Rear Spoiler	1.0%
	Wheel Deflector / Air outlet inside wheel housing	1.0%
	Bumper Lip	1.0%
	Rear Diffuser	2.0%
AERO15	Underbody Cover (Incl. Rear axle cladding)	3.0%
	Lowering ride height by 10mm	2.0%
AERO20	Active Grill Shutters	3.0%
	Extend Air dam	2.0%

[654] Larose, G. et al. 2016. Evaluation of the Aerodynamics of Drag Reduction Technologies for Light-duty Vehicles - a Comprehensive Wind Tunnel Study. SAE International Journal of Passenger Cars - Mechanical Systems. Vol. 9(2): at 772-84. Available at: https://doi.org/10.4271/2016-01-1613. (Accessed: Feb. 12, 2024).
[655] Larose, G. et al. 2016. Evaluation of the Aerodynamics of Drag Reduction Technologies for Light-duty Vehicles - a Comprehensive Wind Tunnel Study. SAE International Journal of Passenger Cars - Mechanical Systems. Vol. 9(2): at 772-84. Available at: https://doi.org/10.4271/2016-01-1613. (Accessed: Feb. 12, 2024).
[656] Chevrolet Product Information. 2015 Chevrolet Colorado. Available at: https://media.chevrolet.com/content/media/us/en/chevrolet/vehicles/colorado/2015/_jcr_content/iconrow/textfile/file.res/15-PG-Chevrolet-Colorado-082218.pdf. (Accessed: Feb. 12, 2024).

Table 3-114: Combinations of Technologies That Could Achieve Aerodynamic Improvements Used in the Current Analyses for Pickup Trucks

Aero Improvements	Components	Effectiveness (%)
AERO5	Whole Body Styling (Shape Optimization)	1.5%
	Faster A pillar rake angle	0.5%
	Rear Spoiler	1.0%
	Wheel Deflector / Air outlet inside wheel housing	1.0%
	Bumper Lip	1.0%
AERO10	Rear Diffuser	2.0%
	Underbody Cover (Incl. Rear axle cladding)	3.0%
AERO15	Active Grill Shutters	3.0%
	Extend Air dam	2.0%

As discussed further in Chapter 3.7, we assume manufacturers apply OC technology at defined rates in the analysis fleet. While the AERO levels in the analysis are technology-agnostic, AERO20 improvements require the use of an OC technology such as active grille shutters.

In this analysis we considered two levels of aerodynamic improvements for the HDPUVs over the associated baselines. Fewer technology levels are considered because HDPUVs have less diversity in overall vehicle shape when compared to the light-duty fleet. Prioritization of functionality of the vehicles forces a boxy shape and limits incorporation of many of the “shaping”-based aerodynamic technologies, such as smaller rear-view mirrors, body air flow, rear diffusers, etc. However, the baseline reference point has been updated in this analysis and represents an overall improvement in aerodynamic technology in this fleet, see Chapter 3.5.2. The update in baseline values for the HDPUV fleet also results in different effectiveness values associated with the HDPUV AERO technology values compared with previous analysis,[657] see Table 3-116 and Table 3-117 below.

We considered the following technologies for the levels of AERO improvements for HDPUVs: The first level of improvement considers minor body styling, air dams, tire spats and possible underbody panel technologies; the second level of improvement considers additional body features such as rear visors, larger under body panels or low-profile roof racks, and active grille shutters. These technology definitions are based on the same definitions used in the Phase II medium-duty and heavy-duty (MDHD) rule.[658] We determined using the legacy technology definitions is reasonable after assembling the baseline HDPUV fleet for this analysis and have identified that many vehicles in the fleet do not yet use these technologies and further improvements are possible.

3.5.2. Aerodynamic Technologies in the Baseline Fleet

For the light-duty analysis, we used a relative performance approach to assign an initial level of aerodynamic drag reduction technology to each vehicle. Each AERO level represents a percent reduction in a vehicle’s aerodynamic drag coefficient (C_d) from a baseline value for its body style. AERO technologies and their definitions, as well as their prevalence in the 2022 light-duty fleet, are given in Table 3-115. For a vehicle to achieve AERO5, the C_d must be at least 5 percent below the baseline for the body style; for AERO10, 10 percent below the baseline, and so on.

[657] Phase II MDHD rule – RIA - Chapter 2.5.4. Available at: https://nepis.epa.gov/Exe/ZyPDF.cgi/P100P7NS.PDF?Dockey=P100P7NS.PDF.
[658] Phase II MDHD rule – RIA - Chapter 2.5.4. Available at: https://nepis.epa.gov/Exe/ZyPDF.cgi/P100P7NS.PDF?Dockey=P100P7NS.PDF.

Table 3-115: Penetration Rates of Aerodynamic Drag Reduction Levels in the 2022 LD Fleet

Technology	Technology Description	Sales Volume	Penetration Rate
AERO0	Baseline aero	3,335,133	23.1%
AERO5	Aero level 1 (5% drag reduction)	4,502,056	31.2%
AERO10	Aero level 2 (10% drag reduction)	5,058,244	35.0%
AERO15	Aero level 3 (15% drag reduction)	660,522	4.6%
AERO20	Aero level 4 (20% drag reduction)	880,274	6.1%

We assigned a body style to every vehicle in the light-duty fleet; available body styles include convertible, coupe, sedan, hatchback, wagon, SUV, pickup, minivan, and van.[659] Similarly, for the heavy-duty pickup and vans (HDPUVs) the body styles are: Chassis cab, cutaway, fleet SUV, work truck, and work van.[660] These assignments do not necessarily match the body styles that manufacturers use for marketing purposes. Instead, we make these assignments based on engineering judgement and the categories used in our modeling, considering how this affects a vehicle's AERO and vehicle technology class assignments. Different body styles offer different utility and have varying levels of baseline-form drag. This analysis considers both frontal area and body style as unchangeable utility factors affecting aerodynamic forces; therefore, the analysis assumes all reduction in aerodynamic drag forces come from improvement in the drag coefficient. We harmonized the assignment of body types with the Autonomie simulation vehicle technology classes to the fullest extent possible.[661]

For this analysis we classified the level of aerodynamic technology application based on the vehicle's coefficient of drag. For each of the fleets considered, light-duty and HDPUV, a baseline coefficient of drag was determined and represents the minimum AERO0 coefficient value. This means if the vehicle has a coefficient of drag greater than the established baseline value, it was classified as AERO0 tech level. For the light-duty analysis fleet, we determined an average baseline drag coefficient for each body style using manufacturers published model year 2015 drag coefficients data, these values are shown in Table 3-116. For the HDPUV analysis fleet we used data from the model year 2019 Chevy Silverado to establish baseline drag coefficients for heavy-duty Pickup body styles, and used an averaged value of data from the model year 2020 Ford Transit and the model year 2022 Ford e-Transit for cargo vans to established baseline drag coefficients for cargo van body styles, see Table 3-117.[662,663]

For each of the AERO technology levels a maximum and minimum coefficient of drag value was determined, such that if the vehicle's coefficient level was less than the maximum value, but greater than the minimum value, it was classified as achieving the AERO technology level. As an example, walking through technology levels from AERO0 to AERO5 for a convertible, AERO5 is assigned when the C_d values reach 0.317 but is still greater than 0.301. AERO10 is assigned when the C_d value reaches 0.301 or less but is still greater than 0.284.

To the extent possible, we used drag coefficients for each vehicle in the analysis fleet from manufacturer specification sheets. However, manufacturers do not consistently report drag coefficients for their vehicles publicly. We used engineering judgment to assign an AERO level where we could not find a publicly available drag coefficient. If we could not manually determine an AERO level, we used values received from manufacturers and used in previous rulemaking analysis, such as data from the model year 2016 or MY2020

[659] See Market Data Input File for LD.
[660] See Market Data Input File for HDPUV.
[661] See Table 2-21 in Chapter 2.3.2 for the table of vehicle attributes used to build the Autonomie baseline vehicle models. That table includes a drag coefficient for each vehicle class.
[662] CAFE Analysis Autonomie Documentation chapter titled "Vehicle and Component Assumptions."
[663] HDPUV body style reference to Aero: Work Van, Work Truck, Cutaway, Chassis Cab, Fleet SUV.

fleet baseline fleet.[664,665] The model year 2016 or model year 2020 drag coefficient values may not accurately reflect the current technology content of newer vehicles but are, in many cases, the most recent data available. The AERO technology penetration values for the analysis fleet are detailed in Table 3-116 for light-duty vehicles and in Table 3-117 for HDPUVs. The estimated technology penetration levels likely overestimate the amount of AERO0, because drag coefficient values are not readily available for many vehicles, resulting in some understatement of the actual aerodynamic technology levels likely applied in the light-duty and HDPUV baseline fleets.

Table 3-116: Baseline Fleet AERO Technologies by Body Style for LD

Body Style	Aero Level & MY 2022 Volume Distribution					
	Labels	AERO0	AERO5	AERO10	AERO15	AERO20
Convertible	Volume Share	67.3%	8.3%	13.0%	11.3%	0.0
	C_d	0.334	0.317	0.301	0.284	0.267
Coupe	Volume Share	59.5%	26.9%	12.7%	0.8%	0.2%
	C_d	0.319	0.303	0.287	0.271	0.255
Hatchback	Volume Share	23.7%	33.4%	18.3%	0.0	24.6%
	C_d	0.333	0.316	0.3	0.283	0.266
Minivan	Volume Share	7.7%	38.9%	53.4%	0.0	0.0
	C_d	0.326	0.31	0.293	0.277	0.261
Pickup	Volume Share	2.7%	24.9%	57.3%	15.2%	0.0
	C_d	0.42	0.399	0.378	0.357	0.336
Sedan	Volume Share	21.1%	42.9%	21.8%	1.9%	12.4%
	C_d	0.302	0.287	0.272	0.257	0.242
Sport Utility	Volume Share	28.9%	29.4%	34.6%	2.2%	4.9%
	C_d	0.363	0.345	0.327	0.309	0.29
Van	Volume Share	0.0	0.0	0.0	77.0%	23.0 %
	C_d	0.389	0.37	0.35	0.331	0.311
Wagon	Volume Share	38.9%	18.0%	0.3%	26.3%	16.4%
	C_d	0.342	0.325	0.308	0.291	0.274

[664] *See* 83 Fed. Reg. 42986 (Aug. 24, 2018). The model year 2016 fleet was built to support the 2018 NPRM.
[665] *See* 87 Fed. Reg. 25710 (May 2, 2022). The model year 2020 fleet was built to support the 2022 Final Rule.

Table 3-117: Baseline Fleet AERO Technologies by Body Style for HDPUVs

Body Style	Aero Level & MY 2022 Volume Distribution					
	Labels	AERO0	AERO5	AERO10	AERO15	AERO20
Work Van 2b	Volume Share	32.6%	0.0%	1.2%	0.0%	66.2 %
	C_d	0.50	0.45	0.45	0.40	0.40
Work Van 3	Volume Share	39.2%	0.0 %	0.0 %	0.0 %	60.8%
	C_d	0.60	0.54	0.54	0.48	0.48
Work Truck 2b*	Volume Share	71.3%	0.0 %	28.7%	0.0 %	0.0 %
	C_d	0.50	0.45	0.45	0.40	0.40
Work Truck 3	Volume Share	72.1 %	0.0 %	27.9%	0.0 %	0.0 %
	C_d	0.60	0.54	0.54	0.48	0.48

*Rivian no longer included in Work Truck 2b category.

Baseline drag coefficients are also utilized in the final assignment of aerodynamic improvement levels. The drag coefficient of each vehicle is compared to the baseline average drag coefficient value for the vehicle's body style to perform the assignment. Note that the highest AERO levels, AERO15 and AERO20, are not considered for certain body styles; see Chapter 3.5.1 for more detail.

Table 3-118: Aerodynamic Application by Manufacturer as a Percent of MY 2022 LD Sales

Manufacturer	AERO0	AERO5	AERO10	AERO15	AERO20
BMW	32.6 %	30.8 %	14.0 %	12.2 %	10.4 %
Ford	4.6 %	2.5 %	81.7 %	11.1 %	0.0 %
GM	8.4 %	18.0 %	73.6 %	0.0 %	0.0 %
Honda	4.1 %	55.2 %	36.1 %	3.4 %	1.2 %
Hyundai	1.8 %	66.1 %	25.9 %	0.0 %	6.2 %
JLR	22.8 %	38.2 %	38.1 %	0.0 %	0.9 %
Karma	100.0 %	0.0 %	0.0 %	0.0 %	0.0 %
Kia	27.6 %	37.5 %	26.1 %	2.9 %	5.8 %
Lucid	0.0 %	0.0 %	0.0 %	0.0 %	100.0 %
Mazda	18.8 %	69.3 %	0.3 %	11.6 %	0.0 %
Mercedes-Benz	28.5 %	6.7 %	19.4 %	5.8 %	39.5 %
Mitsubishi	39.8 %	0.0 %	60.2 %	0.0 %	0.0 %
Nissan	8.8 %	41.8 %	48.1 %	1.2 %	0.0 %
Rivian	0.0 %	0.0 %	100.0%	0.0 %	0.0 %
Stellantis	57.4 %	22.5 %	0.5 %	18.9 %	0.8 %
Subaru	33.4 %	39.0 %	27.6 %	0.0 %	0.0 %
Tesla	0.0 %	0.0 %	0.0 %	0.0 %	100.0 %

Toyota	44.0 %	41.1 %	12.0 %	0.0 %	2.8 %
Volvo	1.8 %	55.8 %	40.9 %	1.6 %	0.0 %
VWA	45.7 %	18.2 %	28.3 %	3.0 %	4.8 %

Table 3-119: Aerodynamic Application by Manufacturer as a Percent of HDPUV Sales

Manufacturer	AERO0	AERO10	AERO20
Ford	59.1%	0.0%	40.9 %
GM	100.0 %	0.0%	0.0%
Mercedes-Benz	0.0%	0.0%	100.0 %
Nissan	0.0%	31.6 %	68.4 %
Stellantis	0.0%	71.5 %	28.5 %

3.5.3. Aerodynamic Technology Adoption Features

We use a relative performance approach to assign current aerodynamic technology level to a vehicle. For some body styles with different utility, such as pickup trucks, SUVs and minivans, frontal area can vary, and this can affect the overall aerodynamic drag forces. To maintain vehicle utility and functionality related to passenger space and cargo space, we assume all technologies that improve aerodynamic drag forces do so by reducing C_d while maintaining frontal area.

Technology pathway logic for levels of aerodynamic improvement consists of a linear progression, with each level superseding all previous ones as explained in Chapter 3.5.1. Note that, as discussed above, the light-duty and HDPUV fleets have different AERO technology pathways based on the technological capabilities of improvements for each set of those vehicle classes.

For the light-duty analysis, the following adoption features apply: the highest levels of AERO are not considered for certain body styles. In these cases, this means that we do not apply AERO15 and AERO20 in the analysis fleet, and the model cannot adopt those AERO levels during simulation. For these body styles, there are no commercial examples of drag coefficients that demonstrate the required AERO15 or AERO20 improvement over baseline levels. We also deem the most advanced levels of aerodynamic drag simulated as not technically practicable given the form drag of the body style and costed technology, especially given the need to maintain vehicle functionality and utility, such as interior volume, cargo area, and ground clearance. As seen in Table 3-113, example technologies that may be used to achieve high AERO levels include lowered ride height, active grill shutters, and extended air dams. Therefore, the analysis does not consider AERO20 for convertibles, pickups,[666] and wagons, and AERO15 and AERO20 for minivans, as a potential pathway to compliance in response to regulatory alternatives.

We also do not allow application of AERO15 and AERO20 technology to vehicles with more than 780 HP. There are two main types of vehicles that inform this threshold: performance ICE vehicles and high-power BEVs. In the case of the former, we recognize that manufacturers tune aerodynamic features on these vehicles to provide desirable downforce at high speeds and to provide sufficient cooling for the powertrain, rather than reducing drag, resulting in middling drag coefficients despite advanced aerodynamic features. Therefore, manufacturers may have limited ability to improve aerodynamic drag coefficients for high performance vehicles with ICEs without reducing HP. Only 4,047 units of sales volume in the baseline fleet include limited application of aerodynamic technologies due to ICE vehicle performance.[667]

In the case of high-power BEVs, the 780-HP threshold is set above the highest peak system HP present on a BEV in the 2020 fleet. We originally set this threshold based on vehicles in the model year 2020 fleet in

[666] Note, we do allow AERO 20 appliation for HDPUVs, but the technology represents an improvement from a much lower technology baseline than the LD baseline.
[667] See the Market Data Input File.

parallel with the 780-HP ICE limitation. For this analysis, the restriction does not have any functional effect because the only BEVs that have above 780-HP in the model year 2022 analysis fleet – the Tesla Model S and X Plaid, and variants of the Lucid Air – are already assigned AERO20 as a baseline technology state and there are no additional levels of AERO technology left for those vehicles to adopt. Broadly speaking, BEVs have different aerodynamic behavior and considerations than ICE vehicles, allowing for features such as flat underbodies that significantly reduce drag.[668] BEVs are therefore more likely to achieve higher AERO levels, so the HP threshold is set high enough that it does not restrict AERO15 and AERO20 application. Note that the CAFE Model does not force high levels of AERO adoption; rather, higher AERO levels are usually adopted organically by BEVs because significant drag reduction allows for smaller batteries and, by extension, cost savings.

For the HDPUV there are no additional adoption features. The technologies available for the fleet are limited in scope for reasons discussed in Chapter 3.5.1, but both AERO technology levels are available to all vehicle body styles.

Note that while many aerodynamic features that contribute to drag reduction (e.g., active grill shutters) are considered OC technologies, AERO levels and the OC program are modeled separately for the analysis. For further discussion of OC technologies, see Chapter 3.7.

3.5.4. Aerodynamic Technology Effectiveness

Effectiveness values for aerodynamic technologies are shown in Figure 3-39 and Figure 3-40 for light-duty vehicles and in Figure 3-41 for HDPUVs. See Chapter 3.5.1 for a discussion about what each aerodynamic technology represents, and how it is considered. As discussed, the analysis assumes aerodynamic drag reduction is only achieved from reduction in C_d and not from reduction of frontal area, to maintain vehicle functionality and utility, such as passenger space, ingress/egress ergonomics, and cargo space.

Each of the effectiveness values shown in Figure 3-39 and Figure 3-40 is representative of the fuel economy improvement expected for a specific technology key to be upgraded from the baseline technology (AERO0) to the available improved AERO technology along the X-axis for each fleet. For example, the AERO20 values shown in the figures represent the range of effectiveness values that can be achieved through the replacement of AERO0 technology with AERO20 technology for every technology combination that is not restricted from using AERO20. Here, we use the change in fuel consumption values between entire technology keys,[669] and not the individual technology effectiveness values. Using the change between whole technology keys captures the complementary or non-complementary interactions among technologies.

[668] 2020 EPA Automotive Trends Report, at 227.
[669] Technology key is the unique collection of technologies that constitutes a specific vehicle see Chapter 3.

Figure 3-39: LD AERO Technology Effectiveness Values for All Vehicle Technology Classes (Unconstrained)

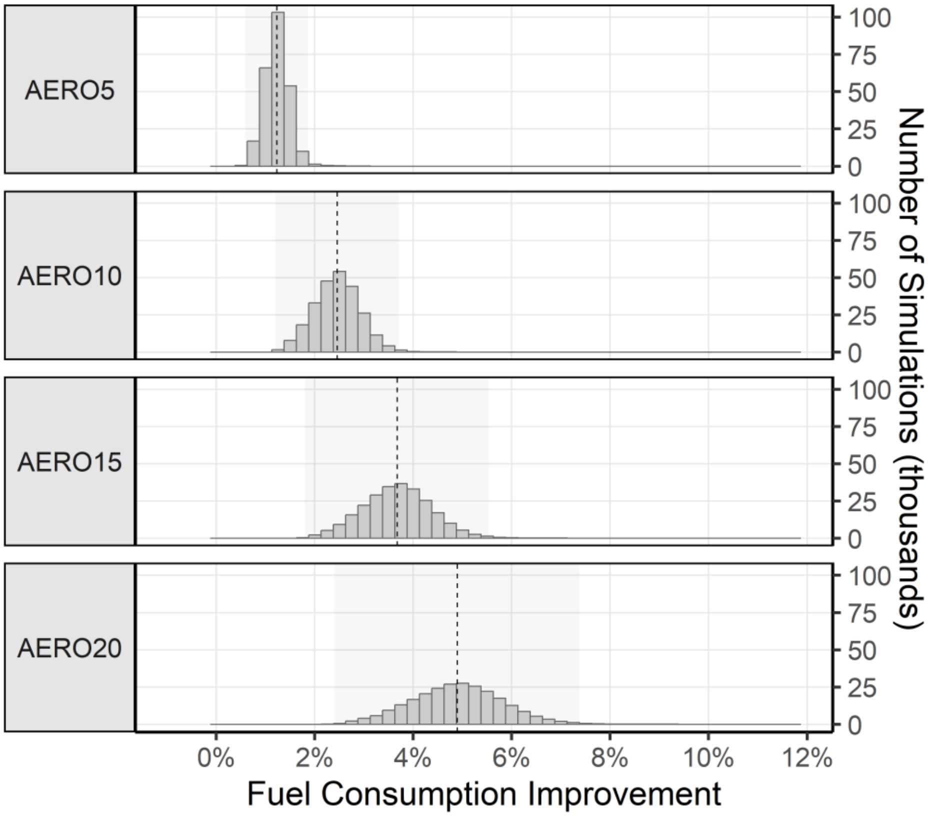


Figure 3-40: LD AERO Technology Effectiveness Values for All Vehicle Technology Classes (Standard Setting)

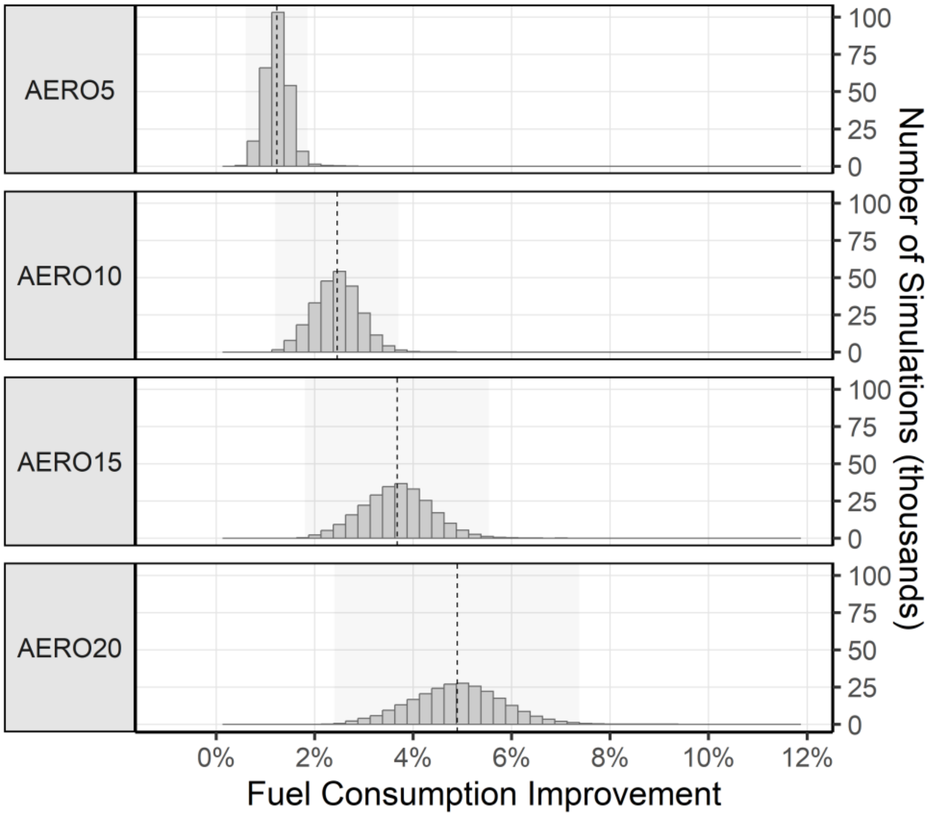
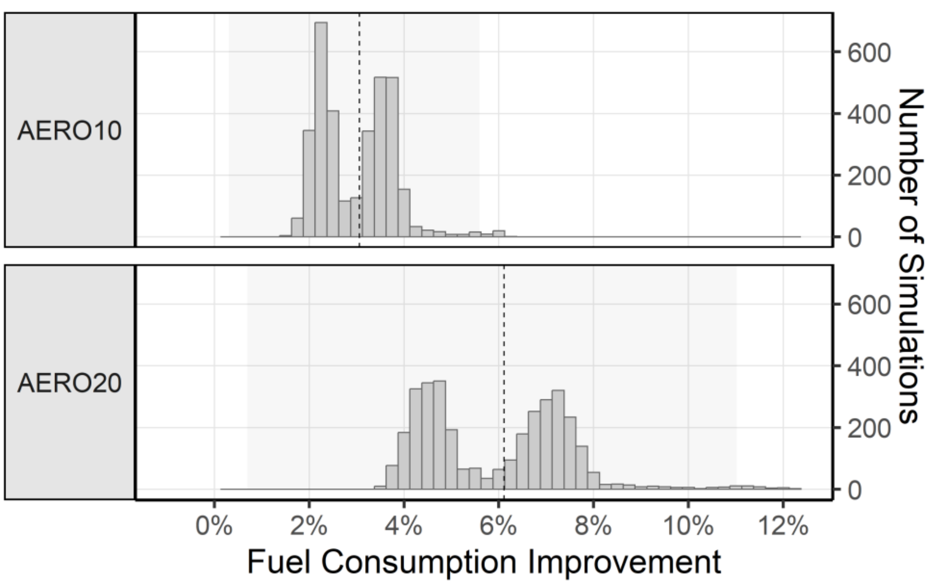


Figure 3-41: HDPUV AERO Technology Effectiveness Values for All Vehicle Technology Classes



3.5.5. Aerodynamic Technology Costs

This analysis carries forward the established AERO technology costs previously used in the 2020 final rule[670] and again into the model year 2024-2026 standards analysis. The cost estimates are based on CBI submitted by the automotive industry in advance of the 2018 CAFE NPRM, and on our assessment of manufacturing costs for specific aerodynamic technologies. See the 2018 PRIA for discussion of the cost estimates.[671] We received no additional comments from stakeholders regarding the costs established in the 2018 PRIA during the model year 2024-2026 standards analysis and continued to use the established costs for this analysis. These costs have been adjusted to reflect the 2021 dollar values, as shown in Table 3-120 and Table 3-121.

For light-duty AERO improvements, the cost to achieve AERO5 is relatively low, as manufacturers can make most of the improvements through body styling changes. The cost to achieve AERO10 is higher than AERO5, due to the addition of several passive aerodynamic technologies, and consecutively the cost to achieve AERO15 and AERO20 are much higher than AERO10 due to use of both passive and active aerodynamic technologies as can be seen from the DMCs listed in Table 3-120 and Table 3-121.

As discussed in Chapter 3.5.1 the two AERO technology levels available for HDPUVs are similar in technology type and application to light-duty vehicles in the same technology categories, specifically light trucks. Because of this similarity, and unlike other technology areas that are required to handle higher loads or greater wear, aerodynamics technologies can be almost directly ported between fleets. As a result, there is no difference in technology cost between light-duty and HDPUV fleets for this analysis.

Table 3-120 and Table 3-121 show the initial DMC values for aerodynamic improvement technologies in model year 2022 reported in 2021$ for light-duty vehicles and HDPUVs respectively. The tables also show the total costs for the technologies across multiple model years, also in 2021$. The total cost includes the application of RPE and learning factors. As shown in the tables, the learning curves for each AERO technology are independent, representing how technologies have become available and are being refined over different time periods. For instance, AERO15 and AERO20 have steeper learning curves because they represent newer technologies that are still improving relatively faster, versus the lower technology levels which are assumed to have been available longer. See the Technologies Input File for all costs across all model years.

Table 3-120: DMC and Total Costs of Aerodynamic Improvement Technology for LDVs (in 2021$) - Includes RPE and Learning Effects

Aero Improvements for Passenger Cars and SUV	DMC (2021$)	Total Cost: Including RPE and Learning Factors (2021$)	
		MY 2022	MY 2030
0%	$0.00	$0.00	$0.00
5%	$48.68	$55.30	$49.19
10%	$99.54	$113.06	$100.56
15%	$248.85	$159.76	$142.10
20%	$649.16	$282.65	$251.40

Table 3-121: DMC and Total Costs of Aerodynamic Improvement Technology for HDPUVs (in 2021$) - Includes RPE and Learning Effects

Aero Improvements for HDPUVs	DMC (2021$)	Total Cost: Including RPE and Learning Factors (2021$)

[670] See the FRIA accompanying the 2020 final rule, Chapter VI.C.5.e.
[671] See the PRIA accompanying the 2018 NPRM, Chapter 6.3.10.1.2.1.2 for a discussion of these cost estimates.

		MY 2022	MY2030
0%	$0.00	$0.00	$0.00
10%	$99.54	$113.06	$100.56
20%	$649.16	$282.65	$251.40

3.6. Tire Rolling Resistance

Tire rolling resistance is a road load force that arises primarily from the energy dissipated by elastic deformation of the tires as they roll. As a tire rolls, at the point the tread makes contact with the pavement, the casing of the tire flattens-out to create the contact patch where it deforms to shape the small peaks and in valleys of pavement. This mechanical interlock between the tire tread and the pavement is what provides grip. Tread deformation should recover rapidly. The faster the tire spins, the faster it must recover to continue to provide a useful level of grip. Temperature of the tread materials influences both the rate at which the tire can deform and recover. Cold tires require more time to deform thus have less traction. Wet roads can rapidly lower tire temperature and therefore such road conditions can also affect deformation and recovery time.

Tire deformation can be categorized into two tiers: deformation of the rubber that makes up the tread as it conforms to the peaks and valleys on the road surface, and the larger flattening-out of the tire casing to make contact with the road surface. There are energies associated with each of these deformations; the first is result of stretching and sliding of the polymer chains from which the rubber is made, and the second is due to flexing the steel cords and belts of the tire casing. These energies combined come out of the energy supplied by the vehicle's powertrain, which is why lower rolling resistance tires improve vehicle fuel economy. This also explains why tires with low pressure have higher rolling resistance than properly inflated tires. In other words, less deformation means less energy lost and less rolling resistance.[672] Lower-rolling-resistance tires have characteristics that reduce frictional losses associated with the energy dissipated mainly in the deformation of the tires under load, thereby improving fuel economy.

Tire design characteristics (for example, materials, construction, and tread design) have a strong influence on the amount and type of deformation and the energy the tire dissipates. Historically, it was thought that traction and rolling resistance worked contrary to one another. Indeed, NHTSA has received comments to past CAFE rules stating that improving ROLL would be detrimental to grip. However, in recent years it has become possible to separately engineer rolling resistance and grip, and to mitigate issues related to stopping distance without raising rolling resistance.[673] Tire manufacturers have done this by selecting different materials (e.g., various types of silica and/or Silanes as reinforcing fillers, and/or higher performance tread compound materials), and by using advanced tire design and tread design features (including with the help of computer simulations).

As shown in Chapter 3.6.2 below, OEMs have increasingly specified low rolling resistance tires for new vehicles. While the characteristics of low rolling resistance tires may influence vehicle performance attributes, such as durability, wet and dry traction, handling, and ride comfort, vehicle manufacturers may also change vehicle suspension tuning and/or suspension design to mitigate any potential impact on those attributes. Separately, low rolling resistance tires are also increasingly available from aftermarket tire vendors.

NHTSA has continued to assess the potential impact of ROLL changes on vehicle safety in conjunction with considering low rolling resistance technology in successive CAFE analyses. We have been following the industry developments and trends in application of rolling resistance technologies to light-duty vehicles. However, as stated in the NAS special report on Tires and Passenger Vehicle Fuel Economy,[674] national

[672] Akutagawa, K. 2017. Technology for Reducing Tire Rolling Resistance. *Japanese Society of Tribologists*. Vol. 12(3): at 99-102. Available at: https://www.jstage.jst.go.jp/article/trol/12/3/12_99/_pdf. (Accessed: Feb. 12, 2024).
[673] Snyder, J. 2008. A Big Fuel Saver: Easy-Rolling Tires (But Watch Braking). Automotive News. Last revised: July 21, 2008. Available at: https://www.autonews.com/article/20080721/OEM01/307219960/a-big-fuel-saver-easy-rolling-tires-but-watch-braking. (Accessed: Feb. 12, 2024).
[674] National Academies of Sciences, Engineering, and Medicine. 2006. Tires and Passenger Vehicle Fuel Economy: Informing Consumers, Improving Performance - - Special Report 286. Available at: https://nap.nationalacademies.org/catalog/11620/tires-and-passenger-vehicle-fuel-economy-informing-consumers-improving-performance. (Accessed: Apr. 1, 2024).

crash data does not provide data about tire structural failures specifically related to tire rolling resistance, because the rolling resistance of a tire at a crash scene cannot be determined. As such, there are currently no data connecting low rolling resistance tires to accident or fatality rates.

Other metrics like brake performance compliance test data are helpful to show trends like that stopping distance has not changed in the last ten years,[675] during which time many manufacturers have installed low rolling resistance tires in their fleet. This means that manufacturers were successful in improving rolling resistance while maintaining stopping distances through tire design and/or tire materials like those discussed above, and/or braking system improvements. In fact, NHTSA's most up-to-date data on ROLL technology shows that there is no degradation in wet grip index values (i.e., no degradation in traction) for tires with improved rolling resistance technology installed on new vehicles.[676] Separately, NHTSA continues to address other tire-related issues through rulemaking,[677] based on research tire problems such as blowouts, flat tires, tire or wheel deficiency, tire or wheel failure, and tire degradation.[678]

The following subchapters discuss levels of ROLL technology that we apply in the CAFE Model, how the technology is assigned in the analysis fleet, adoption features specified to maintain performance, effectiveness, and cost.

3.6.1. Tire Rolling Resistance Reduction Technologies

For this analysis we considered three levels of low rolling resistance tire technology for light-duty vehicles and two levels for HDPUVs. These levels are referred to as ROLL10, ROLL20, and ROLL30. Each level of low rolling resistance tires reduces rolling resistance by 10 percent from an industry-average reference rolling resistance coefficient (RRC) value, referred as ROLL0. Table 3-122 shows the RRC values compared to the reference value for three levels of rolling resistance technology considered in this rule. For example, to achieve ROLL10, the ROLL must be at least 10 percent better than the reference value, which means that the RRC to achieve ROLL10 is 0.0081 or better.

Table 3-122: Tire Rolling Resistance Technologies and Their Associated Rolling Resistance Coefficient

Technology	Rolling Resistance Coefficient (N/N)
ROLL0	0.0090
ROLL10	0.0081
ROLL20	0.0072
ROLL30	0.0063

We used an industry average RRC reference value of 0.009 based on a CONTROLTEC study prepared for the CARB,[679] in addition to CBI submitted by manufacturers prior to the 2018 LD NPRM analysis. The average RRC from surveying 1,358 vehicle models by the CONTROLTEC study is 0.009.[680] The CONTROLTEC study compared the findings of their survey with values provided by the U.S. Tire Manufacturers Association for original equipment tires. The average RRC from the data provided by the U.S. Tire Manufacturers Association is 0.0092,[681] compared to the average of 0.009 from CONTROLTEC.

[675] NHTSA Office of Vehicle Safety Compliance. 2023. Compliance Database. Available at: https://one.nhtsa.gov/cars/problems/comply/index.cfm. (Accessed: Feb. 12, 2024).
[676] The results of these tests are presented in Docket No. NHTSA-2021-0053-0010, Memo to Docket - Rolling Resistance Phase One and Two.
[677] 49 CFR 571.138, Tire pressure monitoring systems.
[678] Choi, E.H. 2012. Tire-Related Factors in the Pre-Crash Phase. Report No. DOT HS 811 617. National Highway Traffic Safety Administration: Washington, D.C. Available at: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/811617. (Accessed: Feb. 12, 2024).
[679] Pannone, G. 2015. Technical Analysis of Vehicle Load Reduction Potential for Advanced Clean Cars. Final Report, April 2015. Available at: https://ww2.arb.ca.gov/sites/default/files/2020-04/13_313_ac.pdf. (Accessed: Feb. 12, 2024).
[680] The RRC values used in this study were a combination of manufacturer information, estimates from coast down tests for some vehicles, and application of tire RRC values across other vehicles on the same platform.
[681] Pannone, G. 2015. Technical Analysis of Vehicle Load Reduction Potential for Advanced Clean Cars. Final Report, April 2015. Available at: https://ww2.arb.ca.gov/sites/default/files/2020-04/13_313_ac.pdf. (Accessed: Feb. 12, 2024).

As stated in the Joint TSD for the 2017-2025 final rule and 2020 final rule, tire technologies that enable rolling resistance improvements of 10 and 20 percent have been in existence for many years.[682] Achieving improvements of up to 20 percent involves optimizing and integrating multiple technologies, with a primary contributor being the adoption of a silica tread technology. Tire suppliers have indicated that additional innovations are necessary to achieve the next level of low rolling resistance technology on a commercial basis, the most important of which are selecting various versions of silica or silanes in place of the carbon black (conventional technology) to reinforce the tire's rubber. In addition, engineers can replace natural rubber with certain variants of emulsion styrene butadiene (E-SBR) rubber or solution styrene butadiene rubber (S-SBR).[683,684] At the cutting edge, scientists are using computer simulations and advanced molecular imaging techniques to better understand how the silica, silanes and S-SBR interact and bond at the molecular level. Through this research it has been discovered that silica and silanes reinforcements enable simultaneous boosts to wet grip and rolling resistance performance because they more homogeneously distribute themselves throughout the S-SBR than would carbon black reinforcements in natural rubber. This results in fewer strain concentrations and reduced energy required during the deformation cycling of the tread compound. Therefore, for a given traction level there is less rolling resistance. Finally, the computer simulation results have allowed tire engineers to select more beneficial versions of silicas, silanes and S-SBR compounds that amplify this effect, resulting in ever lower rolling resistance at higher traction levels.[685,686,687]

In past rulemakings, we did not consider ROLL30 due to lack of widespread commercial adoption of ROLL30 tires in the fleet within the rulemaking timeframe, despite commenters' argument on availability of the technology on current vehicle models and possibility that there would be additional tire improvements over the next decade.[688] Comments we received during the comment period for the model year 2024-2026 light-duty rulemaking also reflected the application of ROLL30 by OEMs, although they discouraged considering the technology due to high cost and possible wet traction reduction. With increasing use of ROLL30 application by OEMs,[689,690,691] and material selection making it possible to design low rolling resistance independent of tire wet grip (discussed above), for this analysis we considered ROLL30 as a viable future technology during this rulemaking period.

We believe that the tire industry is in the process of moving automotive manufacturers towards higher levels of rolling resistance technology in the vehicle fleet. We believe that at this time, the emerging tire technologies that would achieve 30 percent improvement in rolling resistance, like changing tire profile, stiffening tire walls, or adopting improved tires along with active chassis control,[692] among other technologies, will be available for commercial adoption in the fleet during this rulemaking timeframe. As a result, we consider a 30 percent reduction in rolling resistance technology for the light-duty analysis.

Although the NHTSA tire RRC data, CONTROLTEC study, and our existing manufacturer-submitted data included mostly light-duty vehicles, we also used 0.009 as the reference value RRC for ROLL0 for the HDPUVs and indexed ROLL10 and ROLL20 improvements from this value. We have some data showing that HDPUV tires have achieved the same RRC values as light-duty pickup truck tires. For instance, NHTSA's tire RRC data shows that the RRC values for tires tested for the Ford F-150 are in the same range (for these examples in range of ROLL10 and ROLL20) to those values of F-250, although the tire types are different. As

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682 EPA-420-R-12-901, at 3–210.
683 NHTSA DOT HS 811 270.
684 Van Hoek, J. W. et. al. 2019. Implications of the Use of Silica as Active Filler in Passenger Car Tire Compounds of Their Recycling Options. *Materials 2009.* Vol. 12(5): at 725. Available at: https://www.mdpi.com/1996-1944/12/5/725. (Accessed: May 31, 2023).
685 Akutagawa, K. 2017. Technology for Reducing Tire Rolling Resistance. *Japanese Society of Tribologiests*. Vol.12(3): at 99-102 Available at: https://www.jstage.jst.go.jp/article/trol/12/3/12_99/_pdf. (Accessed: Feb. 12, 2024).
686 NHTSA DOT HS 811 270.
687 Amino, N. 2015. Friction & Rolling Resistance of Tyres. *Nippon Gomu Kyokaishi*. Vol. 88(2). at 37–42. Available at: https://doi.org/10.1177/0307174X1504200910. (Accessed: Feb. 12, 2024).
688 NHTSA-2018-0067-11985.
689 Docket No. NHTSA-2021-0053-0010, Evaluation of Rolling Resistance and Wet Grip Performance of OEM Stock Tires Obtained from NCAP Crash Tested Vehicles Phase One and Two, Memo to Docket - Rolling Resistance Phase One and Two.
690 Pannone, G. 2015. Technical Analysis of Vehicle Load Reduction Potential for Advanced Clean Cars. Final Report, April 2015. Available at: https://ww2.arb.ca.gov/sites/default/files/2020-04/13_313_ac.pdf. (Accessed: Feb. 12, 2024).
691 NHTSA DOT HS 811 154.
692 Davari, M. 2015. Rolling resistance and Energy Loss in Tyres. Available at: https://docslib.org/doc/4775729/rolling-resistance-and-energy-loss-in-tyres-mohammad-mehdi-davari-mmdavari-kth-se-kth-vehicle-dynamics-department-of-aeronautical-and-vehicle-engineering. (Accessed: Feb. 12, 2024).

shown in Table 3-123, the RRC for different trims of the Ford F-150 and Ford F-250 ranges from 0.0072 through 0.0086.[693]

Table 3-123: Example of RRC Test Results on Tires of Two LD and HD Truck (Ford F-150 and Ford F-250)

MY – Model – VIN Light-Duty Truck	Type of Tire	ISO28580 RRC (N/kN)	Avg. RRC (N/kN)
2018 Ford F-150 SuperCab - 1FTEX1CB3JFA48191	245/70R17	7.26	7.25
2018 Ford F-150 SuperCab - 1FTEX1CB3JFA48191	245/70R17	7.27	
2018 Ford F-150 SuperCab - 1FTEX1CB3JFA48191	245/70R17	7.21	
2018 Ford F-150 SuperCrew - 1FTEW1CP8JFA14486	275/55R20	7.29	7.23
2018 Ford F-150 SuperCrew - 1FTEW1CP8JFA14486	275/55R20	7.26	
2018 Ford F-150 SuperCrew - 1FTFW1E5XJFA42757	275/55R20	8.37	8.6
2018 Ford F-150 SuperCrew - 1FTFW1E5XJFA42757	275/55R20	8.96	
2018 Ford F-150 SuperCrew - 1FTFW1E5XJFA42757	275/65R18	8.46	
MY – Model Heavy-Duty Truck			
2019 FORD F-250	LT275/70R18	7.41	7.41
2019 FORD F-250	LT275/70R18	7.42	

However, like our analysis for HDPUVs in the Phase 2 final rule, we did not consider ROLL30 for HDPUVs.[694] ROLL30 has limited penetration in the light-duty analysis fleet (see Table 3-124 below), and the only light-duty pickup truck currently using ROLL30 technology is an EV. We also believe that ROLL30 is less likely to be applied to HDPUVs in the rulemaking timeframe because it is a significant added cost for HDPUVs, where manufacturers would see more fuel efficiency benefit from powertrain improvements than rolling resistance improvements. In addition, more of the HDPUV fleet is starting from the first level ROLL0 value (see Table 3-124) than the light-duty fleet. We do not currently have any data showing a pathway to a RRC value of 0.0063 for HDPUVs, but welcome any additional data submitted by stakeholders.

3.6.2. Tire Rolling Resistance Analysis Fleet Assignments

Tire rolling resistance is not a part of tire manufacturers' publicly released specifications and thus it is difficult to assign this technology to the analysis fleet. Manufacturers also often offer multiple wheel and tire packages for the same nameplates, further increasing the complexity of this assignment. We employed an approach consistent with previous rulemaking in assigning this technology, using several data sources and assumptions:

- Throughout the process of building analyses fleets for prior rules (e.g., the 2017 analysis fleet used for the 2018 NPRM), we received RRC values from vehicle manufacturers. We carried over rolling resistance assignments for nameplates where manufacturers had submitted data on the vehicles' rolling resistance values, even if the vehicle was redesigned.
- NHTSA sponsored a ROLL study and used those values in place of any older or missing values.[695]
- We assigned ROLL0 to vehicles for which no information was available from either previous manufacturer submissions or the NHTSA study data.

[693] Docket No. NHTSA-2021-0053-0010. The reason for selecting Ford for this comparison is the wide range of tires tested for RRC by NHTSA for this vehicle.
[694] HD Phase 2 RIA at 2-70, 2-332.
[695] Docket No. NHTSA-2021-0053-0010, Evaluation of Rolling Resistance and Wet Grip Performance of OEM Stock Tires Obtained from NCAP Crash Tested Vehicles Phase One and Two, Memo to Docket - Rolling Resistance Phase One and Two.

- All vehicles under the same nameplate were assigned the same rolling resistance technology level even if manufacturers do outfit different trim levels with different wheels and tires. Based on our experience and manufacturers information provided to us, a manufacturer will most likely use the same tires for the same vehicle under the same nameplate. Therefore, we assigned all vehicles under the same nameplate the same rolling resistance technology level.

Table 3-124 shows the distribution of ROLL technology for both the light-duty and HDPUV fleets. This table shows that the majority of the light-duty fleet has now adopted some form of rolling resistance technology. NHTSA would need further information from manufacturers or other sources to account for any additional ROLL technology in the fleet.

Table 3-124: Distribution of Tire Rolling Resistance Technology for the MY 2022 LDV and HDPUV Fleets

Technology	MY 2022 LD Fleet	HDPUV Fleet
ROLL0	52.9%	76.0%
ROLL10	16.4%	0.0%
ROLL20	24.7%	24.0%
ROLL30	6.0%	N/A

3.6.3. Tire Rolling Resistance Adoption Features

The model can apply rolling resistance technology with either a vehicle refresh or redesign. We recognize that some manufacturers prefer to maintain specific tires with a higher RRC for some performance cars and SUVs. Performance cars and SUVs have higher torque and higher torque causes tire slip. To avoid tire slip, these performance vehicles prefer higher rolling resistance tires. Accordingly, similar to past rulemakings, we applied adoption features based on three different levels of HP limitations: 350hp, 405hp and 500hp, and based on the vehicle's body style (e.g., pickup truck, SUV, wagon, etc.). We applied these cutoffs based on a review of CBI and the distribution of rolling resistance values in the analysis fleet. The following table shows the adoption features applied to low rolling resistance tire technology.

Table 3-125: When Can ROLL Technology Be Applied, Based on Vehicle Body Style and Engine Horsepower

Technology	LD			HDPUV		
Engine HP	≥350	≥405	≥500	≥350	≥405	≥500
ROLL0	All body styles	All body styles	All body styles	All body styles	All body styles	All body styles
ROLL10	All body styles	All body styles	-Pickup truck	All body styles	All body styles	-Work truck
ROLL20	All body styles	-Pickup truck -SUV -Van -Minivan	No body styles	All body styles	-Work truck -Work van -Fleet SUV -Chassis Cab -Cutaway	No body styles
ROLL30	-Pickup truck -Sport Utility -Van	No body styles	No body styles	N/A	N/A	N/A

	-Minivan					

Note that these adoption features are based on the vehicle body styles used in the Autonomie and CAFE modeling, rather than just the regulatory class (e.g., passenger car, light truck, or HDPUV). For example, as shown in the table, ROLL20 can be applied to all light-duty pickup trucks and vans that have an engine HP lower than 500hp. In addition, as discussed above, ROLL30 is not available for vehicles in the HDPUV fleet not because of an adoption feature, but because it is not a technology considered on the HDPUV ROLL technology pathway.

3.6.4. Tire Rolling Resistance Effectiveness

As discussed above, based on the CONTROLTEC study, a thorough review of CBI submitted by industry, and a review of other literature, we used a reference rolling resistance value of 0.009. To achieve ROLL10, the ROLL must be at least 10 percent better than 0.009 (.0081 or better). To achieve ROLL20, the ROLL must be at least 20 percent better than 0.009 (.0072 or better). To achieve ROLL30, the ROLL must be at least 30 percent better than 0.009 (.0063 or better).

We determined effectiveness values for rolling resistance technology adoption using Autonomie modeling. Figure 3-42 through Figure 3-43 below show the range of effectiveness values used for adding ROLL technology to a vehicle in this analysis. The graph shows the change in fuel consumption values between entire technology keys,[696] and not the individual technology effectiveness values. Using the change between whole technology keys captures the complementary or non-complementary interactions among technologies.

The data points with the highest effectiveness values are almost all exclusively BEV and FCEV technology combinations for medium sized non-performance cars. The effectiveness for these vehicles, when the low rolling resistance technology is applied, is amplified by a complementary effect where the lower rolling resistance reduces road load, and the vehicle can use a smaller battery pack (and still meet range requirements). The smaller battery pack reduces the overall weight of the vehicle, further reducing road load, and improving fuel efficiency. All vehicle technology classes experience this complementary effect, but the strongest effect is on the midsized vehicle non-performance classes. By using full vehicle simulations, we can capture effects that demonstrate the full interactions of vehicle technologies.

[696] Technology key is the unique collection of technologies that constitutes a specific vehicle see Chapter 2.3.6.

Figure 3-42: LD Roll Technology Effectiveness Values for All Vehicle Technology Classes (Unconstrained)

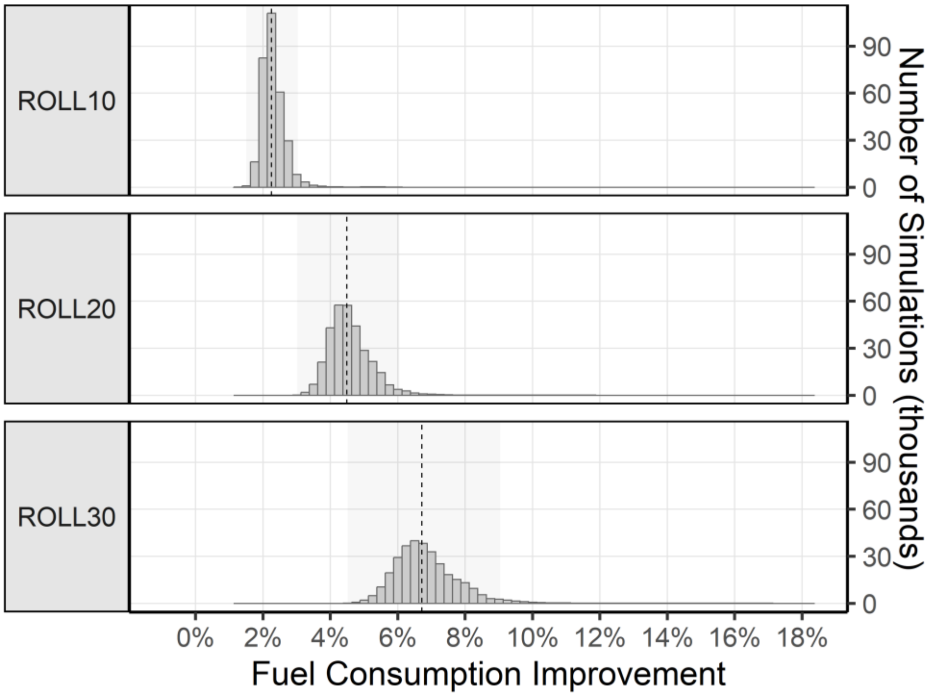


Figure 3-43: LD Roll Technology Effectiveness Values for All Vehicle Technology Classes (Standard Setting)

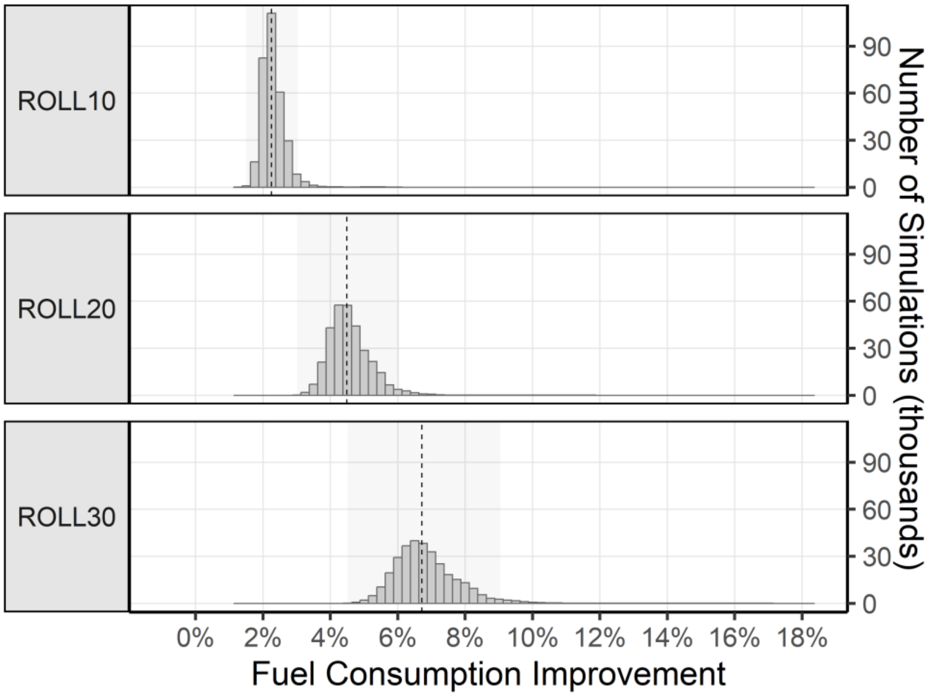
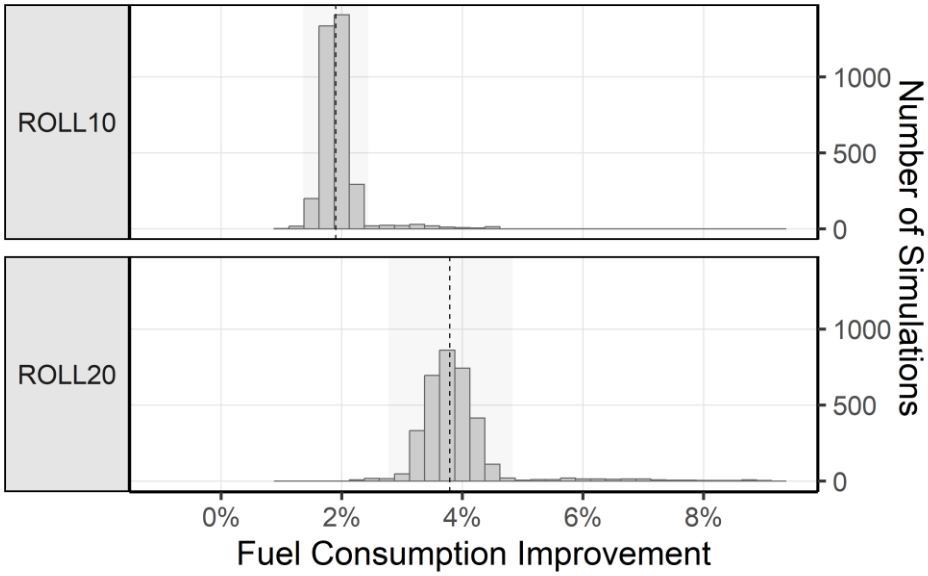


Figure 3-44: HDPUV Roll Technology Effectiveness Values for All Vehicle Technology Classes



3.6.5. Tire Rolling Resistance Costs

The DMC and learning rates for ROLL10 and ROLL20 technology are the same as prior analyses,[697] and the DMC is updated to 2021 dollars. In the absence of ROLL30 DMCs from tire manufacturers, vehicle manufacturers, or studies, to develop the DMC for ROLL30 we extrapolated the DMCs for ROLL10 and ROLL20 then updated them to reflect 2021 dollars. If we receive updated information from tire or vehicle manufacturers on this value, we will update it for future analyses.

We used the same DMCs for the light-duty and HDPUV analyses. This is because the original cost of a potentially heaver or sturdier HDPUV tire is already accounted for in the initial MSRP of a HDPUV in our analysis fleet, and the DMC represents the added cost of the improved tire technology. In addition, as discussed above, light-duty and HDPUV tires are often interchangeable. We believe that the added cost of each tire technology accurately represents the price difference that would be experienced by the different fleets.

Table 3-126 shows the different levels of ROLL technology cost.

Table 3-126: Cost for Tire Rolling Resistance Technologies Relative to ROLL0

Technology	Tire Rolling Resistance Technology Costs (2021$)	
	Direct Manufacturing Cost	Total Cost for MY 2022 (includes RPE and Learning)
ROLL0	$0.00	$0.00
ROLL10	$5.58	$6.47

[697] See NRC/NAS Special Report 286, Tires and Passenger Vehicle Fuel Economy: Informing Consumers, Improving Performance (2006); Corporate Average Fuel Economy for model year 2011 Passenger Cars and Light Trucks, Final Regulatory Impact Analysis (March 2009), at V-137; Joint Technical Support Document: Rulemaking to Establish Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards (April 2010), at 3-77; Draft Technical Assessment Report: Midterm Evaluation of Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards for Model Years 2022-2025 (July 2016), at 5-153 and 154, 5-419. In brief, the estimates for ROLL10 are based on the incremental $5 value for four tires and a spare tire in the NAS/NRC Special Report and confidential manufacturer comments that provided a wide range of cost estimates. The estimates for ROLL20 are based on incremental interpolated ROLL10 costs for four tires (as NHTSA and EPA believed that ROLL20 technology would not be used for the spare tire), and were seen to be generally fairly consistent with CBI suggestions by tire suppliers.

ROLL20	$43.61	$43.43
ROLL30[698]	$86.79	$86.45

3.7. Simulating AC Leakage, AC Efficiency, and Off-Cycle Technologies

AC efficiency and off-cycle technologies can provide fuel economy benefits in real-world vehicle operation, but the required traditional 2-cycle test procedures (i.e., FTP and Highway Fuel Economy Test (HFET)) used to measure fuel economy cannot fully capture those benefits.[699] AC efficiency technologies are technologies that reduce the operation of or the loads on the compressor, which pressurizes AC refrigerant. The less the compressor operates or the more efficiently it operates, the less load the compressor places on the engine or battery storage system, resulting in better fuel efficiency. AC efficiency technologies can include, but are not limited to, blower motor controls, internal heat exchangers, and improved condensers/evaporators. Off-cycle technologies can include, but are not limited to, thermal control technologies, high-efficiency alternators, and high-efficiency exterior lighting.[700]

AC leakage technologies are AC system technologies designed to reduce AC refrigerant leakage over the useful life of the vehicle. Unlike AC efficiency and off-cycle technologies, AC leakage technologies do not provide additional benefits to a vehicle's fuel economy in real-world vehicle operation. While manufacturers can use AC leakage credits to comply with EPA's CO_2 program, they are not permitted to use them to comply with NHTSA's CAFE standards.

Vehicle manufacturers have the option to generate credits for OC technologies and improved AC systems under the EPA's CO_2 program and receive a fuel consumption improvement value (FCIV) equal to the value of the benefit not captured on the 2-cycle test under NHTSA's CAFE program. An FCIV is not a "credit" in the NHTSA CAFE program,[701] but the FCIVs increase the reported fuel economy of a manufacturer's fleet, which is used to determine compliance. EPA applies FCIVs during determination of a fleet's final average fuel economy reported to NHTSA.[702] We only calculate and apply FCIVs at a manufacturer's fleet level, and the improvement is based on the volume of the manufacturer's fleet that contains qualifying technologies.[703]

There are three pathways that manufacturers can use to determine the value of AC efficiency and OC adjustments. First, manufacturers can use a predetermined list or "menu" of g/mi values that EPA has established for specific OC technologies.[704] Second, manufacturers can use 5-cycle testing to demonstrate OC CO_2 benefit;[705] the 3 additional tests (beyond the standard 2 test cycles) allow manufacturers to demonstrate emissions benefits over some elements of real-world driving not captured by the 2-cycle compliance tests (e.g., high speeds, rapid accelerations, hot and cold temperatures, etc.). Third, manufacturers can seek EPA approval, through a notice and comment process, to use an alternative methodology other than the menu or 5-cycle methodology for determining the OC technology improvement values.[706] For this rule, we are removing the second and third pathways for manufacturers claiming OC FCIVs starting in MY2027; however as discussed further below, this has no impact on how we model FCIVs in the CAFE Model. For further discussion of the AC and OC compliance, see Section VI of the preamble.

[698] Roll30 technology is only applied to light-duty vehicles.
[699] *See* 49 U.S.C 32904(c) ("The Administrator shall measure fuel economy for each model and calculate average fuel economy for a manufacturer under testing and calculation procedures prescribed by the Administrator. The Administrator shall use the same procedures for passenger automobiles the Administrator used for model year 1975 (weighted 55 percent urban cycle and 45 percent highway cycle), or procedures that give comparable results.").
[700] 40 CFR 86.1869-12(b) - Credit available for certain OC technologies.
[701] Unlike, for example, the statutory overcompliance credits prescribed in 49 U.S.C. 32903.
[702] 49 U.S.C. 32904(c)-(e). EPCA granted EPA authority to establish fuel economy testing and calculation procedures. See Peamble Section VI for more information.
[703] 40 CFR 600.510-12(c).
[704] *See* 40 CFR 86.1869-12(b). The TSD for the 2012 final rule for MYs 2017 and beyond provides technology examples and guidance with respect to the potential pathways to achieve the desired physical impact of a specific OC technology from the menu and provides the foundation for the analysis justifying the credits provided by the menu. The expectation is that manufacturers will use the information in the TSD to design and implement OC technologies that meet or exceed those expectations in order to achieve the real-world benefits of OC technologies from the menu.
[705] *See* 40 CFR 86.1869-12(c). EPA proposed a correction for the 5-cycle pathway in a separate technical amendment rulemaking. *See* 83 Fed. Reg. 49344 (Oct. 1, 2019). EPA is not approving credits based on the 5-cycle pathway pending the finalization of the technical amendments rule.
[706] *See* 40 CFR 86.1869-12(d).

NHTSA and EPA have been collecting data on the application of these technologies since implementing the AC and OC programs.[707,708] Most manufacturers are applying AC efficiency and OC technologies in their light-duty fleets; in model year 2021, 17 manufacturers employed AC efficiency technologies and 19 manufacturers employed OC technologies, though the level of deployment varies by manufacturer.[709]

However, currently the agency is not assigning FCIVs to any vehicles in the modeled HDPUV fleet. The agency has received petitions from manufacturers for off cycle credits for these vehicles, but to date, none have been approved. Therefore, AC and OC FCIVs were not considered in the HDPUV analysis.

Manufacturers have only recently begun including detailed information on OC and AC efficiency technologies equipped on vehicles in compliance reporting data. For this analysis, though, such information was not sufficiently complete to support a detailed representation of the application of OC technology to specific vehicle model/configurations in the model year 2022 fleet. To account for the AC and OC technologies equipped on vehicles and the potential that manufacturers will apply additional AC and OC technologies in the rulemaking timeframe, we specify model inputs for AC efficiency and OC FCIV in grams/mile for each manufacturer's fleet in each model year. We estimate future values based on an expectation that manufacturers already relying heavily on these adjustments would continue do so, and that other manufacturers would, over time, also approach the limits on adjustments allowed for such improvements.

The next subchapters discuss how the CAFE Model simulates the effectiveness and cost for AC leakage, AC efficiency, and OC technology adjustments.

3.7.1. AC Leakage, AC Efficiency, and Off-Cycle Effectiveness Modeling in the CAFE Model

The CAFE Model uses the AC leakage,[710] AC efficiency, and off-cycle FCIVs to develop a CAFE compliance value that has been adjusted to account for the improvements associated with those technologies.[711] In the analysis and after the first model year, AC efficiency and OC FCIVs apply to each manufacturer's regulatory fleet after the CAFE Model applies conventional technologies for a given standard. That is, conventional technologies are applied to each manufacturers' vehicles in each model year to assess the 2-cycle sales weighted harmonic average CAFE rating. Then, the CAFE Model assesses the CAFE rating to use for a manufacturer's compliance value after applying the AC efficiency and OC FCIVs designated in the Market Data Input File. This assessment of adoption of conventional technology and the AC efficiency and OC technology occurs on a year-by-year basis in the CAFE Model. The CAFE Model attempts to apply technologies and flexibilities in a way that both minimizes cost and allows the manufacturer to meet their standards without over or under complying.[712]

Due to an increase in the production of BEVs as well as ZEV requirements from other regulatory agencies, the analytical "no-action" reference baseline against which we measure the costs and benefits of our standards (see Chapter 1.4) includes an appreciable number of BEVs. This progression of BEVs has propelled a change to how we apply OC benefits to the vehicles in our analysis. Several of the OC technologies available on EPA's "menu" are engine- or transmission-specific (i.e., engine idle start-stop, active transmission and engine warm-up, and high-efficiency alternator technologies). As previously mentioned, BEVs are not equipped with a traditional engine or transmission; therefore, they are not eligible to receive a benefit from technologies in those categories. As a result, we developed a methodology to limit the potential OC benefits for BEVs to the appropriate OC technologies (i.e., BEVs can still receive a benefit

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[707] *See* 77 Fed. Reg. 62832, 62839 (Oct. 15, 2012). EPA introduced AC and OC technology credits for the CO_2 program in the MYs 2012-2016 rule and revised the program in the model year 2017-2025 rule and NHTSA adopted equivalent provisions for MYs 2017 and later in the model year 2017-2025 rule.
[708] EPA. 2023. Vehicle and Engine Certification. Compliance Information for Light-Duty Gas (GHG) Standards. Available at: https://www.epa.gov/ve-certification/compliance-information-light-duty-greenhouse-gas-ghg-standards. (Accessed: February 12, 2024).
[709] 2022 Automotive Trends Report., at 92-95.
[710] As previously mentioned, manufacturers can use AC leakage credits to comply with EPA's CO_2 program but not with the CAFE program. When the CAFE Model is configured to evaluate compliance with only the CAFE program, the system does not include the costs or credits associated with AC leakage technologies in its calculations. However, the model will consider them when it is configured to simultaneously evaluate compliance with both programs. For more discussion on how the CAFE Model incorporates AC leakage, AC efficiency, and off-cycle technologies into its compliance modeling, see Chapter Two S5.4 of the CAFE Model Documentation.
[711] 49 CFR 531.6 and 49 CFR 533.6 Measurement and Calculation procedures.
[712] See CAFE Model Documentation.

associated with high efficiency lighting, solar panels, active aerodynamic improvement, and thermal control technologies).

To determine how manufacturers might adopt AC efficiency and OC technologies in the rulemaking timeframe, we used data from EPA's 2022 Trends Report and CBI compliance data from manufacturers.[713,714] We used manufacturer's model year 2021 AC efficiency and OC FCIVs achieved via the "menu" as a starting point, and then extrapolated values to each model year until model year 2032, for light trucks to the regulatory cap, for each manufacturer's fleets by regulatory class.

To determine the rate at which to extrapolate the addition of AC and OC technology adoption for each manufacturer, we used historical AC and OC technology applications, each manufacturer's fleet composition (i.e., breakdown between passenger cars and light trucks), availability of AC and OC technologies that manufacturers could still use, and manufacturer CBI compliance data. Different manufacturers showed different levels of historic AC efficiency and OC technology adoption; therefore, different manufacturers hit the regulatory caps for AC efficiency technology for both their passenger car and light truck fleets, and different manufacturers hit caps for OC technologies in the light truck regulatory class.

We did not extrapolate OC technology adoption for passenger cars to the regulatory cap for a few reasons. First, previous EPA Trends Reports show that many manufacturers did not adopt OC technology in their passenger car fleets. In addition, manufacturers limited their passenger car offerings in model year 2021 as compared to historical trends based on data in EPA's 2022 Trends Report.[715] Lastly, manufacturer CBI compliance data available to us indicate a lower adoption rate of menu item OC technologies for passenger cars compared to light trucks.

For ICE vehicles, we limited the application of OC credits to 10 g/mi for passenger cars from model year 2020 through model year 2026 and 10 g/mi for light trucks from model year 2020 through model year 2022; however, to align with EPA's CO_2 program, we allowed light trucks to apply 15 g/mi of OC FCIVs from model year 2023 through model year 2026. For BEVs, we set the maximum allowable benefit to 5.0 g/mi for passenger cars and 9.0 g/mi for light trucks for model year 2023-2026. We limit the application of OC FCIVs for ICE vehicles in both the passenger car and light truck fleets to 10.0 g/mi from model year 2027 through model year 2030, 8.0 g/mi in model year 2031, and 6.0 g/mi in model year 2032. Starting in model year 2027, BEVs in both the passenger car and light truck fleets are no longer eligible for OC FCIVs and are assigned a value of 0.0 g/mi to align with the limited range of allowable OC technologies available to BEVs. The inputs for AC efficiency technologies for non-BEVs are set to 5.0 g/mi and 7.2 g/mi for passenger cars and light trucks, respectively, and continue through our rulemaking years for this analysis. For BEVs, AC efficiency technologies are limited to 5.0 g/mi for passenger car and 7.2 g/mi for light trucks from model year 2020 through model year 2026 and go to 0.0 g/mi in model year 2027 and beyond.

We apply FCIVs in this way because the AC and OC technologies are generally more cost-effective than other technologies. The details of this assessment (and the calculation) are further discussed in the CAFE Model Documentation.[716]

To properly account for OC, the model calculates a sales-weighted average between BEVs and non-BEVs by regulatory class (i.e., passenger car and light truck) for each manufacturer and model year in our analysis. The model then calculates the maximum OC benefit for each manufacturer based on the maximum allowable limits for BEVs and non-BEVs in each manufacturer's fleet.[717] These results represent a more accurate accounting of OC benefits given the number of BEVs in the regulatory "no-action" reference baseline. We still allow OC adoption to be applied to PHEVs in this analysis as they still have an ICE. However, the benefits are weighted for the gas operation of the vehicle in the analysis based on the utility factor.

Table 3-127 and Table 3-128 below presents AC leakage, AC efficiency, and off-cycle credits (in g CO_2/mi) for passenger cars and light trucks in this analysis. The credit values in Table 3-126 and Table 3-127 are the

[713] EPA. 2023. Vehicle and Engine Certification. Compliance Information for Light-Duty Gas (GHG) Standards. Available at: https://www.epa.gov/ve-certification/compliance-information-light-duty-greenhouse-gas-ghg-standards. (Accessed: February 12, 2024).
[714] 49 U.S.C. 32907.
[715] 2023 EPA Trends Report Tables 5.7, 5.8, 5.9, and 5.10.
[716] CAFE Model Documentation, Chapter Two S5.
[717] CAFE Model Documentation, Chapter Two S5.1.3.

achievable values we've estimated for each manufacturer, which are maintained in the Market Data Input File. These credit values have not been subjected to their applicable caps; the credit caps, which are discussed above, are maintained in the Scenarios Input File. See Chapter Two S5.4 of the CAFE Model Documentation for more discussion on how the CAFE Model incorporates AC leakage, AC efficiency, and off-cycle technology achievable values and credit caps into its compliance modeling.

Table 3-127: AC Leakage, AC Efficiency, and Off-Cycle Adjustments (in g CO_2/mi) for Passenger Cars

Manufacturer	Adjustment Type	Passenger Car MY										
		2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
BMW	AC Leakage	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	8.3	9.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
Mercedes - Benz	AC Leakage	11.2	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	2.0	2.5	3.0	4.0	5.0	6.0	6.0	6.0	6.0	6.0	6.0
Stellantis	AC Leakage	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	4.9	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	6.0	6.5	7.0	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5
Ford	AC Leakage	13.6	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	9.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
GM	AC Leakage	13.3	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	4.8	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	8.5	9.0	9.5	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
Honda	AC Leakage	13.5	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	4.0	4.5	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	6.0	6.5	7.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
Hyundai	AC Leakage	12.6	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	4.0	4.5	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	4.8	5.0	5.0	5.5	6.0	7.0	7.0	7.0	7.0	7.0	7.0
Kia	AC Leakage	13.7	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	4.0	4.5	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0

	Off-Cycle	4.8	5.0	5.0	4.5	5.0	6.0	6.0	6.0	6.0	6.0	6.0
JLR	AC Leakage	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	7.0	7.0	8.0	8.0	8.0	10.0	10.0	10.0	10.0	10.0	10.0
Mazda	AC Leakage	9.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	3.0	4.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	4.0	4.5	5.0	5.5	6.0	6.0	6.0	6.0	6.0	6.0	6.0
Mitsubishi	AC Leakage	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	4.7	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	2.5	2.5	2.7	3.0	3.2	3.2	3.2	3.2	3.2	3.2	3.2
Nissan	AC Leakage	12.5	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	3.5	4.0	4.5	5.5	6.0	6.0	6.0	6.0	6.0	6.0	6.0
Subaru	AC Leakage	11.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	4.6	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	3.6	4.1	4.4	5.6	6.2	6.2	6.2	6.2	6.2	6.2	6.2
Tesla	AC Leakage	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Toyota	AC Leakage	12.4	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	6.0	7.0	8.5	9.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
Volvo	AC Leakage	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	4.2	4.5	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	4.6	5.0	6.0	6.5	7.0	7.0	7.0	7.0	7.0	7.0	7.0
VWA	AC Leakage	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8

	AC Efficiency	4.5	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	6.0	6.5	7.0	7.5	8.0	8.0	8.0	8.0	8.0	8.0	8.0
Karma	AC Leakage	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Lucid	AC Leakage	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	AC Efficiency	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	Off-Cycle	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Rivian	AC Leakage	-	-	-	-	-	-	-	-	-	-	-
	AC Efficiency	-	-	-	-	-	-	-	-	-	-	-
	Off-Cycle	-	-	-	-	-	-	-	-	-	-	-

Table 3-128: AC Leakage, AC Efficiency, and Off-Cycle Credit Adjustments (in g CO_2/mi) for Light Trucks

Manufacturer	Adjustment Type	Light Truck MY										
		2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
BMW	AC Leakage	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	10.0	13.5	14.0	15.0	15.0	10.0	10.0	10.0	10.0	10.0	10.0
Mercedes - Benz	AC Leakage	14.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	3.0	3.5	4.0	5.5	6.5	8.5	9.0	10.0	10.0	10.0	10.0
Stellantis	AC Leakage	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	7.0	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	10.0	15.0	15.0	15.0	15.0	10.0	10.0	10.0	10.0	10.0	10.0
Ford	AC Leakage	17.1	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2

	Off-Cycle	10.0	14.0	15.0	15.0	15.0	10.0	10.0	10.0	10.0	10.0	10.0
GM	AC Leakage	17.1	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	7.1	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	10.0	13.0	14.0	15.0	15.0	10.0	10.0	10.0	10.0	10.0	10.0
Honda	AC Leakage	17.1	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	10.0	14.0	15.0	15.0	15.0	10.0	10.0	10.0	10.0	10.0	10.0
Hyundai	AC Leakage	12.5	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	5.0	5.0	5.5	6.0	7.0	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	9.0	9.0	9.0	10.0	11.0	10.0	10.0	10.0	10.0	10.0	10.0
Kia	AC Leakage	16.6	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	6.0	6.5	7.0	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	9.0	9.9	9.0	9.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
JLR	AC Leakage	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	10.0	12.0	13.0	14.0	15.0	10.0	10.0	10.0	10.0	10.0	10.0
Mazda	AC Leakage	13.5	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	3.0	4.0	5.0	6.0	7.0	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	7.0	8.0	9.0	10.0	11.0	10.0	10.0	10.0	10.0	10.0	10.0
Mitsubishi	AC Leakage	16.4	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	7.0	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	5.2	5.2	5.2	5.2	5.2	5.2	5.2	5.2	5.2	5.2	5.2
Nissan	AC Leakage	13.4	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	6.5	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	8.0	8.5	9.0	10.0	11.0	10.0	10.0	10.0	10.0	10.0	10.0
Subaru	AC Leakage	16.0	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2

	AC Efficiency	6.8	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	8.5	9.0	10.0	11.0	12.0	10.0	10.0	10.0	10.0	10.0	10.0
Tesla	AC Leakage	16.1	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	5.0	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	6.0	7.0	8.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0
Toyota	AC Leakage	14.9	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	10.0	10.0	12.0	13.0	15.0	10.0	10.0	10.0	10.0	10.0	10.0
Volvo	AC Leakage	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	7.0	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	9.3	10.0	11.0	12.0	13.0	10.0	10.0	10.0	10.0	10.0	10.0
VWA	AC Leakage	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	6.6	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	Off-Cycle	10.0	13.5	14.0	14.5	15.0	10.0	10.0	10.0	10.0	10.0	10.0
Karma	AC Leakage	-	-	-	-	-	-	-	-	-	-	-
	AC Efficiency	-	-	-	-	-	-	-	-	-	-	-
	Off-Cycle	-	-	-	-	-	-	-	-	-	-	-
Lucid	AC Leakage	-	-	-	-	-	-	-	-	-	-	-
	AC Efficiency	-	-	-	-	-	-	-	-	-	-	-
	Off-Cycle	-	-	-	-	-	-	-	-	-	-	-
Rivian	AC Leakage	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	AC Efficiency	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3
	Off-Cycle	5.3	5.3	5.3	5.3	5.3	5.3	5.3	5.3	5.3	5.3	5.3

3.7.2. AC Leakage, AC Efficiency, and Off-Cycle Costs

The CAFE Model applies AC leakage,[718] AC efficiency, and off-cycle technologies independent of the technology pathways detailed in Chapter 3.1 through Chapter 3.6. Instead, the model applies those technologies based on the extrapolated credit values in Table 3-127 and Table 3-128. Similarly, the CAFE Model accounts for the AC leakage, AC efficiency, and off-cycle costs independent of the technologies applied via the technology pathways. For that reason, we place AC leakage, AC efficiency, and off-cycle technology total costs in the Scenarios File rather than the Technologies File. Below, we describe how we developed the AC leakage, AC efficiency, and off-cycle technology total costs used in our analysis.

In its 2010 Final Regulatory Impact Analysis (FRIA),[719] EPA estimated that AC leakage technologies would have a DMC of $15.00 per vehicle (in 2002$) in model year 2012 and AC efficiency technologies would have a DMC of $51.00 per vehicle (in 2005$) in model year 2012. In their 2010 Final TSD, EPA and NHTSA described AC leakage and AC efficiency technologies as having time-based learning that reduces costs at three percent per year.[720] In their 2012 Final TSD,[721] EPA and NHTSA amended the DMC for AC Efficiency technologies by adding an additional $15.00 per vehicle (in 2010$) to the initial DMC in model year 2017.

To facilitate adding the new DMC for AC efficiency technologies to the initial estimate, we used GDP Price Deflators to convert the initial DMC from 2005$ to 2021$ and the new DMC from 2010$ to 2021$. We then applied a learning factor of 0.85[722] to translate the effective date of the initial DMC from model year 2012 to model year 2017. Next, we added the new DMC to the initial DMC and calculated a total DMC for AC efficiency technologies to be $77.30 per vehicle (in 2021$) in model year 2017.

We then used a GDP Price Deflator to convert the DMC for AC leakage technologies from 2002$ to 2021$ and applied a learning factor of 0.85[723] to translate the effective date of the initial DMC from model year 2012 to model year 2017. We calculated the DMC for AC leakage technologies to be $18.67 per vehicle (in 2021$) in model year 2017. Table 3-129 contains a summary of the AC leakage and AC efficiency technology DMCs.

Table 3-129: AC Leakage and AC Efficiency Technology DMCs for PCs and LTs

	Initial	Initial	New	Initial	New	Total
Technology	DMC [2002$ / veh] in MY 2012	DMC [2005$ / veh] in MY 2012	DMC [2010$ / veh] in MY 2017	DMC [2021$ / veh] in MY 2017	DMC [2021$ / veh] in MY 2017	DMC [2021$ / veh] in MY 2017
AC Leakage	$15.00	N/A	N/A	$18.67	N/A	$18.67
AC Efficiency	N/A	$51.00	$15.00	$58.79	$18.51	$77.30

As previously mentioned, the DMCs for AC leakage and AC efficiency technologies are in dollars per vehicle; however, the CAFE Model requires a unit DMC (in dollars per grams of CO_2/mile) as an input. To convert the DMCs (in dollars per vehicle) for AC leakage and AC efficiency technologies to a unit DMC (in dollars per grams of CO_2/mile), we divided them by an appropriate credit value (in grams of CO_2/mile). In their 2012 Final TSD, EPA and NHTSA estimated an average AC leakage credit value of 6.3 grams of CO_2/mile for passenger cars and an average AC efficiency credit value of 5.0 grams of CO_2/mile for passenger cars and light trucks in model year 2017. To simplify our calculations, we set the estimated average AC leakage credit

[718] As previously mentioned, manufacturers can use AC leakage credits to comply with EPA's CO2 program but not with the CAFE program. When the CAFE Model is configured to evaluate compliance with only the CAFE program, the system does not include the costs or credits associated with AC leakage technologies in its calculations. However, the model will consider them when it is configured to simultaneously evaluate compliance with both programs. For more discussion on how the CAFE Model incorporates AC leakage, AC efficiency, and off-cycle technologies into its compliance modeling, see S5.4 of the CAFE Model Documentation.

[719] Final Rulemaking to Establish Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards Regulatory Impact Analysis for MYs 2012–2016.

[720] Final Rulemaking to Establish Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards Joint Technical Support Document for MYs 2012–2016.

[721] Joint Technical Support Document: Final Rulemaking for 2017-2025 Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards.

[722] Using the learning curve from the 2010 Final TSD, we started with a learning factor of 1.00 in model year 2012 and reduced it three percent per year to model year 2010, which yielded a learning factor of 0.85 in model year 2017.

[723] Using the learning curve from the 2010 Final TSD, we started with a learning factor of 1.00 in model year 2012 and reduced it three percent per year to model year 2010, which yielded a learning factor of 0.85 in model year 2017.

value for light trucks equal to that of passenger cars in model year 2017. Using these credit values, we calculated the unit DMC for AC leakage technologies to be $2.96 per gram of CO_2/mile for passenger cars and light trucks and the unit DMC for AC efficiency technologies to be $15.46 per gram of CO_2/mile for passenger cars and light trucks, in 20121$ in model year 2017.

Next, we applied a learning factor of 0.94[724] to the AC leakage and AC efficiency unit DMCs to translate them from model year 2017 to model year 2020, which is the first cost model year in the Scenarios File. We calculated the final unit DMC for AC leakage technologies to be $2.79 per gram of CO_2/mile for passenger cars and light trucks in model year 2020 and the unit DMC for AC efficiency technologies to be $14.55 per gram of CO_2/mile for passenger cars and light trucks, in 2021$ in model year 2020. Finally, we adjusted the unit DMCs for RPE, and applied learning factors to estimate total costs for model years 2020 through 2050.[725] Table 3-130 contains a summary of the AC leakage and AC efficiency technology credit values, unit DMCs, and model year 2020 total cost. Table 3-132 contains AC leakage and AC efficiency technology total costs for model years 2022 through 2032.

Table 3-130: AC Leakage and AC Efficiency Technology Credit Value, Unit DMCs, and MY 2020 Total Cost for PCs and LTs

Technology	DMC [2021$ /veh] in MY 2017	Credit Vals [g CO_2/mi] in MY 2017	Unit DMC [2021$ / g CO_2/mi] in MY 2017	Unit DMC [2021$ / g CO_2/mi] in MY 2020	Total Cost [2021$ / g CO_2/mi] in MY 2020
AC Leakage	$18.67	6.3	$2.96	$2.79	$4.18
AC Efficiency	$77.30	5.0	$15.46	$14.55	$21.83

In its 2016 Proposed Determination TSD, EPA estimated that the off-cycle technology level 2 package, which contains 3.0 grams of CO_2/mile, would have a unit DMC of $55.00 per gram CO_2/mile (in 2013$) for passenger cars and light trucks in model year 2017.[726] We used a GDP Price Deflator to convert the original unit DMC from 2013$ to 2021$. We calculated the unit DMC for off-cycle technologies to be $64.14 per gram CO_2/mile for passenger cars and light trucks, in 2021$ in model year 2017.

Next, we applied a learning factor of 0.94[727] to the off-cycle technology unit DMCs to translate them from model year 2017 to model year 2020, which is the first model year in the analysis. We calculated the final unit DMC (in 2021$) for off-cycle technologies to be $55.99 per gram of CO_2/mile for passenger cars and light trucks in model year 2020 in model year 2020. Finally, we adjusted the unit DMC for RPE, and applied learning factors to estimate total costs for model years 2020 through 2050.[728] Table 3-131 contains a summary of the off-cycle technology credit value, unit DMCs, and model year 2020 total cost. Table 3-132 contains off-cycle technology total costs for model years 2022 through 2032.

Table 3-131: Off-Cycle Technology Credit Value, Unit DMCs, and MY 2020 Total Cost for PCs and LTs

Technology	Credit Vals [g CO_2 / mi] in MY 2017	Unit DMC [2013$ / g CO_2/mi] in MY 2017	Unit DMC [2021$ / g CO_2/mi] in MY 2017	Unit DMC [2021$ / g CO_2/mi] in MY 2020	Total Cost [2021$ / g CO_2/mi] in MY 2020
Off-Cycle	3.0	$55.00	$64.14	$59.99	$89.98

724 The learning factor for AC Leakage and AC Efficiency technologies in model year 2020 is 0.94, which was in the 2020 Final Rule for MYs 2021 through 2026.
725 Although the final model year in the study period is model year 2050, the final model year in the Scenarios File in model year 2040. The Model assumes the total costs for AC leakage, AC efficiency, and off-cycle technologies remain constant from model year 2041 through model year 2050.
726 Proposed Determination on the Appropriateness of the Model Year 2022-2025 Light-Duty Vehicle Greenhouse Gas Emissions Standards under the Midterm Evaluation: Technical Support Document.
727 The learning factor for AC Leakage and AC Efficiency technologies in model year 2020 is 0.94, which was in the 2020 Final Rule for MYs 2021 through 2026.
728 Although the final model year in the study period is model year 2050, the final model year in the Scenarios File in model year 2040. The Model assumes the total costs for AC leakage, AC efficiency, and off-cycle technologies remain constant from model year 2041 through model year 2050.

Table 3-132: AC Leakage, AC Efficiency, and Off-Cycle Technology Total Costs in 2021$ per Gram of CO_2 per Mile

Reg Class	Technology	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
Passenger Car	AC Leakage	$4.01	$3.93	$3.85	$3.78	$3.70	$3.63	$3.56	$3.48	$3.41	$3.35	$3.28
	AC Efficiency	$20.96	$20.54	$20.13	$19.73	$19.33	$18.95	$18.57	$18.20	$17.83	$17.48	$17.13
	Off-Cycle	$87.15	$85.46	$84.33	$83.19	$81.95	$80.72	$79.51	$78.31	$77.14	$75.98	$74.84
Light Truck	AC Leakage	$4.01	$3.93	$3.85	$3.78	$3.70	$3.63	$3.56	$3.48	$3.41	$3.35	$3.28
	AC Efficiency	$20.96	$20.54	$20.13	$19.73	$19.33	$18.95	$18.57	$18.20	$17.83	$17.48	$17.13
	Off-Cycle	$87.15	$85.46	$84.33	$83.19	$81.95	$80.72	$79.51	$78.31	$77.14	$75.98	$74.84

4. Consumer Response to Manufacturer Compliance Strategies

4.1. Macroeconomic Assumptions that Affect and Describe Consumer Behavior

The comprehensive economic analysis of CAFE and fuel efficiency standards included in this rule requires a detailed and explicit explanation of the macroeconomic context in which regulatory alternatives are evaluated. NHTSA continues to rely on projections of future fuel prices to evaluate manufacturers' use of fuel-saving technologies, the resulting changes in fuel consumption, and various other benefits. Furthermore, the analysis includes modules projecting future demand for light-duty vehicle travel, sales of new cars and light trucks, and the retirement of used vehicles under each regulatory alternative. Constructing these forecasts requires explicit projections of macroeconomic and demographic variables, including U.S. GDP and Personal Disposable Income, consumer confidence, and U.S. population and household formation.

CAFE Model Files Referenced in this Chapter

Below is a list of CAFE Model Files referenced in this chapter. See Chapter 2.1.9 "Where to Find the Internal NHTSA Files?" for a full list of files referenced in this document and their respective file locations.

- Parameters Input File
- CAFE Model Input File
- CAFE Model Documentation

4.1.1. Gross Domestic Product and Other Macroeconomic Assumptions

For this analysis NHTSA employs forecasts of future fuel and electricity prices from the EIA 2023 AEO.[729] An agency within the U.S. Department of Energy (DOE), EIA collects, analyzes, and disseminates independent and impartial energy information to promote sound policymaking, efficient markets, and public understanding of energy and its interaction with the economy and the environment. EIA uses NEMS to produce its AEO, which presents forecasts of future fuel prices, among many other energy-related variables. AEO projections of energy prices and other variables are not intended as predictions of what will happen; rather, they are projections of the likely course of these variables that reflect their past relationships, specific assumptions about future developments in global energy markets, and the forecasting methodologies incorporated in NEMS. Each AEO includes a "Reference Case" as well as a range of alternative scenarios that each incorporate somewhat different assumptions from those underlying the Reference Case.

In addition to forecasts of future fuel prices, NHTSA's CAFE Model relies on the S&P Global Insight forecasts of population, total number of U.S. households, and the University of Michigan Index of Consumer Sentiment, to project new vehicle sales in future model years, retirement rates for used vehicles, and aggregate demand for VMT.[730] All other macroeconomic variables used in these forecasts are projected using the 2023 AEO Reference Case.

EIA relies on the S&P Global Insight forecasts of these and other macroeconomic variables to develop the energy demand forecasts in NEMS, so the fuel and electricity price forecasts NHTSA obtains from EIA are consistent with the Global Insight economic forecasts.[731] For example, the EIA 2023 AEO forecast for fuel prices relies on the September 2022 Global Insight forecast. We updated the projections of U.S. households, and consumer sentiment used in the CAFE Model with the September 2022 S&P Global Insight forecast. While the September 2023 vintage of this forecast represents a more up-to-date projection of the macroeconomic inputs, it also represents a significant change from the economic conditions used to inform EIA's projections in the 2023 AEO. As a result, using the September 2022 projections produces a more

[729] At the time that NHTSA conducted its analysis the 2023 AEO was the most recent vintage of the report available. Data from the 2023 AEO can be accessed at https://www.eia.gov/outlooks/aeo/tables_ref.php.
[730] Global Insight data are available on a fee basis at https://www.spglobal.com/marketintelligence/en/mi/industry/economics-country-risk.html.
[731] EIA uses S&P Global's US model to forecast macroeconomic variables used in NEMS to forecast energy production, demands and prices. In an iterative process, NEMS energy assumptions are used to simulate S&P Global's US model.

internally consistent overall set of inputs. Table 4-1 presents the projections to 2050 for each of these macroeconomic inputs used for this current rulemaking's central analysis.

Table 4-1: Macroeconomic Assumptions

Year	GDP (Billion $2018)	U.S. Households (Millions)	Consumer Sentiment	U.S. Population (Millions)	Real Disposable Personal Income (Billion $2012)
2019	20,998	127.5	96.0	330.4	14,756
2020	20,282	127.9	81.5	331.5	15,676
2021	21,432	129.0	77.6	332.0	16,021
2022	21,789	130.0	57.3	333.1	15,161
2023	21,958	131.2	70.5	334.5	15,696
2024	22,170	132.4	83.8	336.1	16,141
2025	22,516	133.7	92.7	337.7	16,518
2026	22,992	134.9	96.9	339.4	16,897
2027	23,469	136.1	96.5	341.1	17,395
2028	23,919	137.2	94.3	342.8	17,809
2029	24,328	138.3	92.2	344.5	18,168
2030	24,703	139.4	91.2	346.2	18,570
2031	25,089	140.5	91.3	347.8	19,003
2032	25,543	141.6	91.8	349.5	19,448
2033	26,040	142.8	92.7	351.1	19,930
2034	26,538	144.0	92.9	352.6	20,369
2035	27,041	145.1	92.8	354.1	20,832
2036	27,576	146.2	92.7	355.5	21,314
2037	28,140	147.3	92.9	356.9	21,839
2038	28,719	148.4	93.2	358.2	22,367
2039	29,308	149.5	93.4	359.5	22,905
2040	29,951	150.5	93.6	360.8	23,470
2041	30,597	151.6	93.4	362.0	24,029
2042	31,248	152.6	93.3	363.1	24,614
2043	31,912	153.6	93.3	364.3	25,206
2044	32,575	154.6	93.4	365.4	25,816
2045	33,240	155.6	93.7	366.5	26,451
2046	33,921	156.7	93.8	367.6	27,099
2047	34,629	157.7	93.9	368.7	27,765
2048	35,347	158.6	93.8	369.8	28,435

2049	36,074	159.7	93.7	370.9	29,118
2050	36,853	160.7	93.5	371.9	29,841

As is evident from inspecting the forecasts in Table 4-1, 2020 was an unusual year. The table shows significant decreases in both real GDP and consumer confidence between 2019 and 2020, but an increase in real disposable personal income (RDPI). While the former reflects the reduction in employment and economic output during the early stages of the COVID-19 pandemic and the response of consumer sentiment to those developments, the increase in disposable income was a consequence of large-scale economic assistance from the U.S. government to households to aid them in coping with the consequences of the pandemic. Real GDP began to climb again in 2021, increased further in 2022, and is projected to grow steadily thereafter. In contrast, disposable income fell slightly in 2022 with the retreat in temporary economic assistance but is expected to grow steadily starting in 2023.

In spite of the return to macroeconomic growth in 2021, consumers' perceptions of the economy, as measured by the University of Michigan's Survey of Consumers, remained relatively pessimistic compared to historical levels.[732] The share of Americans who viewed their financial situation as improving over the past year plummeted during the latter part of 2021 and during the first half of 2022, as elevated inflation levels, growing borrowing costs, declines in households' wealth, and other developments weighed on their minds.[733] Perceptions have improved since then; the University of Michigan's index of consumer sentiment reached a level of 70 by the end of 2023. While this is about 10 points higher than its level at the end of 2022, it remains well below levels seen in the years leading up to the COVID-19 pandemic. Price growth also slowed significantly in 2023, with headline inflation falling to about 3.1 percent by the end of the year, and consumer expectations about future price growth have also slowed significantly. Even as inflation rates have declined since their high-points in mid-2022, current prices remain a significant concern to consumers. A little under half of those surveyed in late 2023 identified higher prices as the reason for a decline in their personal finances.[734] This is down slightly from its highpoint in 2022, but still more than double the levels seen in the years leading up to the pandemic. While volatile, gasoline prices were also expected to rise by a growing share of American consumers over both the short and long term since the start of the Russia-Ukraine War.[735] Confidence is expected to rise in future years to levels seen just before the start of the COVID-19 pandemic, however, it faces significant short-term headwinds.

Thus, the economic context of 2024 suggests consumer confidence has begun to tick upward but has not yet returned to its 2019 levels even as other measures of economic well-being including inflation have improved. The first year simulated in this analysis is 2023, though the agency relies on observational data (rather than forecasts) for 2023 to the greatest extent possible. The elements of the analysis that rely most heavily on the macroeconomic inputs – aggregate demand for VMT, new vehicle sales, and used vehicle retirement rates – all reflect projections of the economy's relatively rapid return to pre-pandemic growth rates in 2023 and beyond, as well as the lingering concerns of consumers.

4.1.2. Energy Prices

Fuel prices influence a number of critical elements of the agency's analysis. They influence consumers' demands for increased fuel economy in the absence of regulatory pressure, influence the relative attractiveness of competing technologies available to manufacturers to improve fuel economy (which considers the value of fuel savings to buyers of new cars and trucks), affect the amount of travel in light-duty vehicles, and determine the value of each gallon saved by raising CAFE standards. In this analysis, NHTSA updated the fuel price forecast to AEO 2023 Reference Case.[736] While fuel prices are one of the most critical

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[732] Data from the University of Michigan Surveys of Consumers can be accessed at http://www.sca.isr.umich.edu/.
[733] University of Michigan Surveys of Consumers. Chart 6: Current Financial Situation Compared with a Year Ago. Available at: https://data.sca.isr.umich.edu/charts.php. (Accessed: Feb. 13, 2024).
[734] See University of Michigan Surveys of Consumers. Chart 7a: Higher Prices as Reasons for Worse Personal. Available at: https://data.sca.isr.umich.edu/charts.php. (Accessed: Dec. 12, 2023).
[735] See University of Michigan Surveys of Consumers. Chart 39: Expected Change in Gasoline Prices During the Next Year and Chart 40: Expected Change in Gasoline Prices During the Next 5 Years. Available at: https://data.sca.isr.umich.edu/charts.php. (Accessed: Dec. 12, 2023).
[736] The agency's modeling shows fuel cell vehicles accounting for a negligible share of the on-road fleet through 2050, so hydrogen price inputs do not materially affect the analysis.

inputs to the analysis, they are also one of the least certain – particularly over the extended lifetimes of the vehicles affected by this rulemaking.

NHTSA has actively engaged in CAFE rulemakings over the last two decades, and in each of its actions forecasted fuel prices have borne little resemblance to those actually observed during the ensuing years. As Figure 4-1 illustrates, fuel price forecasts have generally declined in each successive rulemaking analysis but have still consistently overestimated the trajectory of actual prices. Overestimating the price of fuel will make improvements to fuel economy more privately beneficial in the analysis. An exception to this is the forecast used to analyze the 2022 Final Rule, which predicted that gas prices would remain at relatively low levels and did not anticipate the sharp rebound in prices in 2021. With that said, prices have since declined to levels closer to earlier pre-pandemic forecasts. Overall, the results of CAFE analyses are vulnerable to uncertainty in both directions where future fuel prices are concerned.

EIA regularly produces a retrospective analysis that evaluates the performance of its previous fuel price projections, measuring the degree of both under and over prediction and absolute prediction error.[737] The Congressional Budget Office compared the performance of various oil price forecasts and found, unsurprisingly, that most forecasts performed better over shorter periods of time.[738] In addition, NHTSA recently determined that assuming a fixed real price performed as well at predicting future prices as EIA's projections. However, this analysis requires fuel price projections spanning several decades, and EIA is generally recognized as an authoritative source for projections of future developments in energy markets. While we continue to use EIA's projections in this analysis, we recognize that future fuel prices may differ from those assumed here and address this possibility through extensive sensitivity analysis.

[737] The most recent EIA retrospective analysis is available at https://www.eia.gov/outlooks/aeo/retrospective/pdf/retrospective.pdf.
[738] Gecan, R. 2020. CBO's Oil Price Forecasting Record. Working Paper. Congressional Budget Office: Washington, D.C. Available at: www.cbo.gov/publication/56356. (Accessed: Feb. 13, 2024).

Figure 4-1: Real Gasoline Price Forecasts in CAFE Rulemakings and Observed Prices[739]

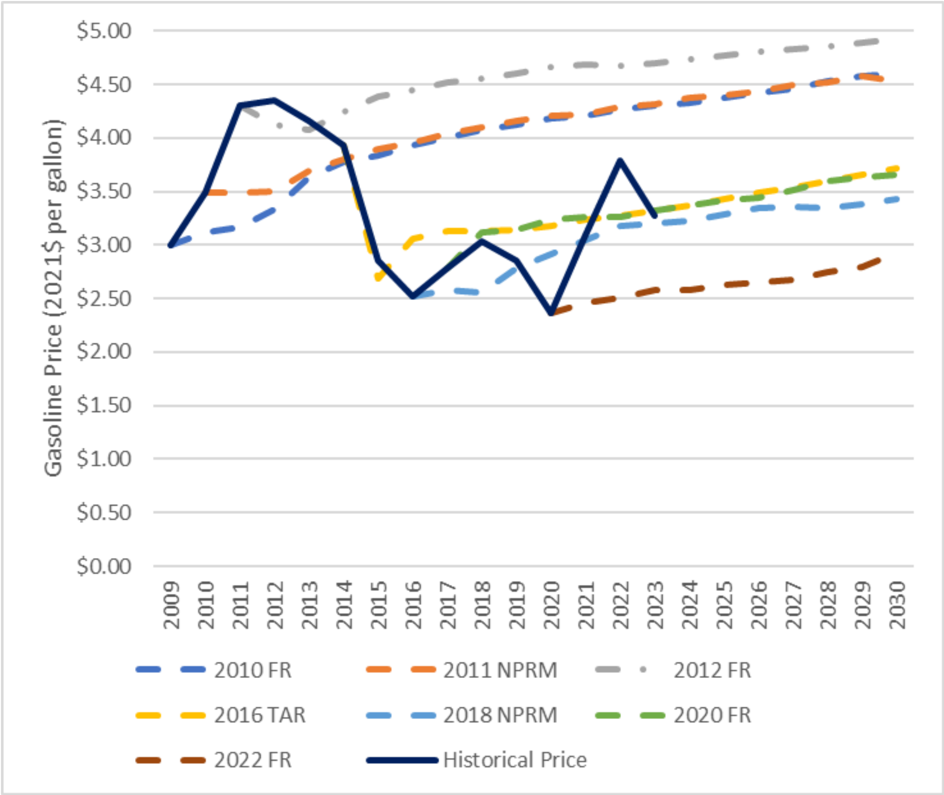
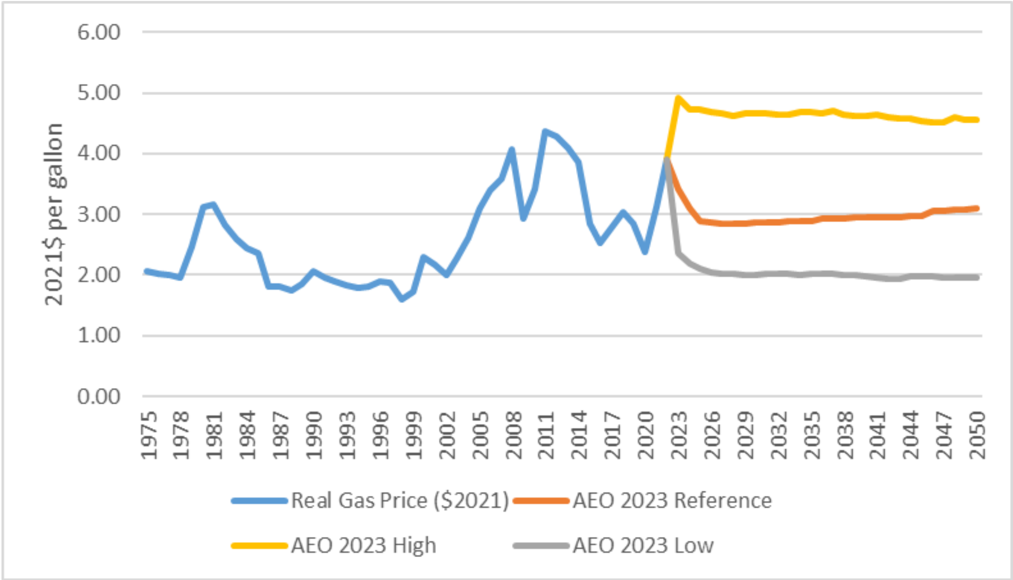


Figure 4-2 displays the High, Low, and Reference fuel price projections from AEO 2023 alongside historical, real gasoline prices dating back to the inception of the CAFE program. The central analysis supporting this final rule uses the AEO 2023 Reference Case fuel price projections (for all fuel types except hydrogen), but we consider the AEO Low and High Oil price cases as bounding cases for sensitivity analyses. The purpose of the sensitivity analyses, discussed in greater detail in FRIA Chapter 9, is not to posit a more credible future state of the world than the reference baseline – we assume the reference baseline is the most likely future state – but rather to measure the degree to which important outcomes could change under different assumptions about fuel prices.

739 Real prices are expressed in 2021 dollars. Historical price for gasoline is taken from the EIA.

Figure 4-2: Real Fuel Price Assumptions in Historical Context



4.2. Fleet Composition

The size and composition of the on-road fleet is a critical element of the analysis for both CAFE and fuel efficiency standards. The technology added by manufacturers to meet more stringent CAFE and fuel efficiency standards will influence the price of new vehicles. As a consequence, consumers may respond by changing the type or specific model of the new vehicle they buy or buying a used vehicle in lieu of a new vehicle. These decisions will affect how long older vehicles remain in the fleet, as well as how many miles are driven in total by new and used vehicles of different ages. Each model year cohort (or "vintage") of cars and light trucks fleet is dynamically simulated within the CAFE Model, and its evolution over time responds to regulatory alternatives, fuel prices, tax incentives, and macroeconomic conditions that affect its size, composition, and usage.

The following subchapters discuss how new vehicle sales of cars, light trucks, and HDPUVs– the annual addition of new vehicles to the fleet or registered population–are likely to evolve over future model years under the No-Action Alternative and differ in response to the regulatory alternatives analyzed by this final rule. The discussion then moves on to consider the influence of increasing durability of new vehicles and of changing economic conditions on the rate at which used vehicles of different vintages and ages are retired from service under the No-Action Alternative and identify the potential influence of the individual regulatory alternatives the agency considers on scrappage rates and the number and use of older vehicles.

NHTSA models new vehicle sales and scrappage of used vehicles independently. As discussed in more detail in preamble Section II.E., we believe accounting for interactions between the new and used vehicle markets, and the demand for VMT, would be better modeled jointly, but we are not utilizing such an approach for this final rule because we have so far been unable to develop a satisfactory model that does so. While noting the benefits of modeling these two effects jointly, we believe our approach captures the sources of changes in fleet composition that are attributable to changing CAFE and fuel efficiency standards and allows policymakers to make informed opinions about the consequences of alternative stringency levels.

4.2.1. Changes in New Vehicle Sales

The CAFE Model currently operates as if all costs incurred by the manufacturer to meet regulatory obligations are "passed through" to buyers of new vehicles in the form of higher selling prices.[740] These costs include

[740] The question of cost pass-through is one that academic and industry researchers have considered for decades. We explore some these theories in FRIA Chapter 7.

those for installing additional technology on vehicles to comply with fleetwide fuel economy or fuel efficiency targets, a scaler markup of direct manufacturing costs to capture indirect costs of additional capital equipment and overhead, as well as any civil penalties paid when fleets fail to meet these targets. Costs to add technologies that reduce fuel consumption should increase vehicle prices, but that technology will also generate a stream of future fuel savings that consumers should be willing to pay for according to their own preferences – and preferences for consumption now versus future consumption in particular. The extent to which higher prices that result from raising the stringency of CAFE and fuel efficiency standards suppress sales that otherwise would have occurred is unsettled amongst academics, but the direction of the impact is well supported.

To isolate the impact of the standards, the CAFE Model breaks the sales response module into three discrete components. The first predicts the evolution of the overall size of the light-duty and HDPUV fleets under reference baseline conditions, which include prevailing standards, and forecasts demographic and macroeconomic growth. The second measures how the combination of changes in vehicle prices, tax incentives earned, and fuel economy or fuel efficiency levels contributes to differences in sales among regulatory alternatives. By modeling sales in the first step as a function of macroeconomic conditions, and then applying an independent own-price elasticity to estimate the change in sales across alternatives, the model is able to more clearly distinguish between sales expected in future years under those reference baseline conditions and incremental changes in sales changes from their reference baseline level under each alternative. The third step determines how market shares of light trucks and passenger cars in the light-duty fleet are likely to evolve under reference baseline conditions, and how changes in their relative prices among regulatory alternatives are likely to affect those shares.

4.2.1.1. How NHTSA Models Consumer Willingness to Pay for Fuel Savings

To model changes in new vehicle sales in response to more stringent fuel economy and fuel efficiency standards, NHTSA must account for two effects: 1) higher fuel economy technology levels will likely increase the cost of vehicles, and 2) reduced fuel costs will make vehicles more attractive to consumers and increase demand for them. Therefore, NHTSA must make some assumptions about consumer's willingness to pay (WTP) for future fuel savings to estimate the impact of the rule on new vehicle sales.

Chapter 2 of the FRIA contains an extensive discussion of consumer's WTP for fuel efficiency-improving technology, including a discussion of the extent to which market failure explains consumer behavior, behavioral economic perspectives, a literature review, and empirical estimates from the literature of consumer's willingness-to-pay. That discussion highlights that there are several reasons why consumers may not be willing to pay $1 at the time of vehicle purchase for every $1 dollar in fuel savings over the life of the vehicle. At the very least, consumers generally prefer consumption today over consumption in the future and would be expected to discount future fuel savings according to their own preferences.[741] As such, it is appropriate to model consumer WTP at less than the full lifetime value of the expected fuel savings.[742]

The CAFE Model uses the same assumptions about consumer valuation of fuel economy in the No-Action Alternative and under each regulatory alternative. Specifically, it assumes that potential buyers value fuel savings from buying a higher-mpg model over only the first 30 months they own and drive it, and that manufacturers will only make improvements in fuel economy that repay their initial costs over that same 30-month period. This 30-month period is based upon what manufacturers have consistently told the agency in the past about how new vehicle buyers value expected fuel savings. NHTSA assumes that this holds for buyers in both the light-duty and the HDPUV markets.

NHTSA explicitly assumes that: 1) consumers are willing to pay for fuel economy improvements that pay back within the first 2.5 years of vehicle ownership (at average usage rates); 2) manufacturers know this and will provide these improvements even in the absence of regulatory pressure; 3) the amount of technology for which buyers will pay rises (or falls) with rising (or falling) fuel prices; 4) consumer WTP is the same with or

[741] Note, however, that the so-called "energy efficiency paradox" describes the observed behavior of consumers not paying $1 in increased upfront purchase costs for at least $1 in *present-value, discounted* fuel savings.
[742] As discussed in Chapter 2 of the FRIA, there is no consensus on the extent to which consumers discount future fuel savings, whether consumers discount future fuel savings appropriately or "undervalue" them, the extent to which this discounting is a market failure, and the nature of that market failure if one exists.

without higher fuel economy standards; and 5) these fuel savings are considered when evaluating the impact of new vehicle prices on vehicle purchase and retirement decisions.

Depending on the discount rate buyers are assumed to apply, the agency's assumption that buyers value savings in fuel costs over only the first 30 months they own a more fuel-efficient model amounts to assuming that they value 25-30 percent of its expected lifetime savings in fuel costs. These savings would offset only a fraction of the expected increase in new vehicle prices that the agency estimates would be required for manufacturers to recover their increased costs for making the improvements to fuel economy and fuel efficiency its standards would require. Under this assumption, raising standards will cause sales of vehicles to decline, prices for used vehicles to increase, and the retirement of older vehicles and their replacement by newer models to slow.

Importantly, NHTSA's assumptions regarding how consumer's value fuel savings at the time of new vehicle purchase do not apply to how NHTSA values future fuel savings in its societal benefit-cost analysis. NHTSA's benefit cost analysis includes the full lifetime fuel savings discounted using 3 and 7 percent discount rates.

4.2.1.2. Modeling the Fleetwide Sales Response

For purposes of regulatory evaluation, the relevant sales metric is the difference between alternatives in the number of new cars, light trucks, and HDPUVs sold each year rather than the absolute number of sales under any of the alternatives. Recognizing this, the sales response component of NHTSA's CAFE model currently includes four components: (1) a reference baseline forecast of the level of sales for each regulatory class of vehicle (based upon forecast macroeconomic inputs for light-duty vehicle, and external projections of changes in total sales for HDPUV); (2) a price elasticity that creates overall sales differences among regulatory alternatives (which have different effects on new vehicle prices) relative to that reference baseline in each year; (3) a projection of changes in the *shares* of passenger cars and light trucks in the reference baseline light-duty fleet; and (4) a price-based adjustment that produces differences in the passenger car and light truck market shares of light-duty vehicle sales in each alternative.

The structure of the sales module reflects the idea that total new vehicle sales are primarily driven by conditions in the economy that are exogenous to the automobile industry. Over time, new vehicle sales have been highly cyclical, rising when prevailing economic conditions are positive (periods of growth) and falling during periods of economic contraction. While the changes to vehicle model offerings and their features that occur as a result of manufacturers' compliance efforts have some influence on the total volume of new vehicle sales, their effect is modest compared to that of economic factors. Instead, they cause the marginal differences among regulatory alternatives that the current sales module is designed to simulate – more expensive vehicles generally reduce total sales, but only marginally.

The first component of the sales response model is the nominal forecast, which, for light-duty vehicles, is a function (with a small set of inputs) that determines the size of the new vehicle market in each calendar year in the analysis for the reference baseline. It is of some relevance that this statistical model is intended only as a means to project sales under the reference baseline. The reference baseline sales nominal forecasting model does not include prices and is not intended for statistical inferences about price responses in the new vehicle market.

The reference baseline forecast for light-duty vehicles is derived from a statistical model (Equation 4-1 and Table 4-2 below) that includes a set of exogenous macroeconomic factors affecting new light-duty vehicle sales. Sales of HDPUVs were excluded from this projection due to inconsistencies between the response of past HDPUV and light-duty sales levels to macroeconomic conditions.[743] Instead, NHTSA used a combination of compliance data and EIA's 2023 AEO to forecast HDPUV reference baseline sales. NHTSA considered using a statistical model drawn from the light-duty specification to project new HDPUV sales but reasoned that the mix of HDPUV buyers and vehicles was sufficiently different that an alternative approach was required. Due to a lack of historical and future data on the changing customer base in the HDPUV market (e.g., the composition of commercial and personal users) and uncertainty around vehicle classification

[743] Specifically, NHTSA found that HDPUV sales were significantly less correlated with macroeconomic indicators than are light duty sales. NHTSA, therefore, has much less confidence in the output of a similar model forecasting HDPUV sales.

at the light-duty vehicle and HDPUV margin, the agency chose to rely on an exogenous forecast path from the AEO.

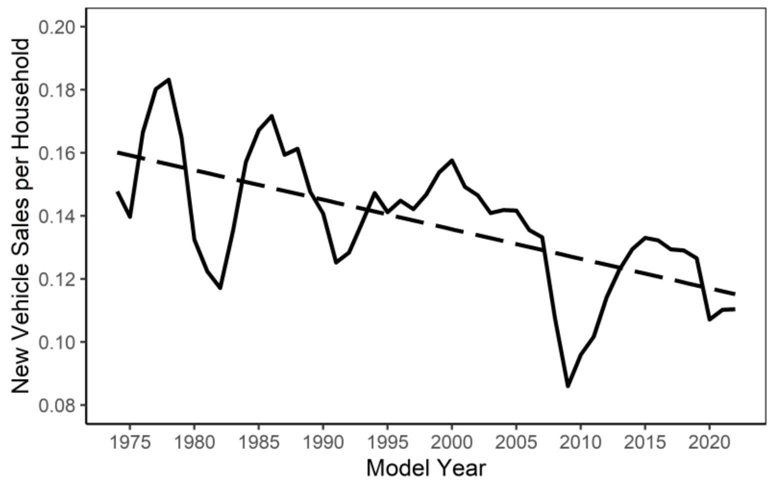
To determine sales for the HDPUV analysis fleet in MY2022, we used sales figures from manufacturers' compliance data from various vintages (spanning model years 2014-2022, varying by manufacturer). For future model years, we applied EIA's projected percent change in sales to the new HDPUV fleet size, with an upward adjustment of 2 percent for model years 2023-2025, and 2.5 percent for model years 2026-2028. The adjustment to the AEO forecast was necessary to reconcile the differences between the analysis fleet's size and AEO's model year 2022 fleet size.[744] Instead of adjusting the fleet size to match AEO's in MY2022, the agency elected to phase-in the increase in growth rates over a span of years to reflect that HDPUV production may continue to face supply constraints resulting from the COVID-19 pandemic in the near future, but should return to normal sometime later in the decade.

As the equation and table show, NHTSA's light-duty sales model accounts for the number of households in the United States, recent number of new vehicles sold, GDP, and consumer confidence. The structure of the forecast model is a time-series autoregressive distributed lag specification, a form that is widely used in forecasting. To reflect the fact that households are the primary unit of demand for new vehicles, the dependent variable is defined as new vehicles sold per household.[745] While this variable still exhibits the cyclical behavior that new vehicle sales exhibit over time, the trend shows the number of new vehicles sold per household declining since the 1970s, as shown in Figure 4-3, where the dotted line is the trend over time. This is in part driven by the decline in average household size during this time period, from 3 household members to around 2.5.[746]

Statistical testing (using the augmented Dickey-Fuller unit root test) revealed that the models' dependent variable is non-stationary,[747] so its value during the previous year is included as an explanatory variable in the regression equation. In addition, the model includes a lagged variable that represents the three-year running sum of new vehicle sales, divided by the number of households in the previous year. This variable attempts to capture the potential that some households may "overshoot" their desired vehicle ownership levels by purchasing additional cars or light trucks during periods of robust income growth, but then avoid making repeat purchases for some period. As vehicles' durability and prices have increased over time, and the average length of initial ownership has increased similarly, this variable puts downward pressure on sales after successive years of high sales (particularly during extrapolation).

[744] The analysis fleet size being smaller than current projection is attributable to the compliance data used to construct the fleet covering nearly a decade worth of sales. Given long-term growth trends and the cyclical nature of HDPUV sales, it is reasonable that our analysis fleet size was lower than current MY2022 projections.
[745] U.S. Census Bureau. 2023. Number of U.S. Households Is Taken From Federal Reserve Economic Data. Available at: https://fred.stlouisfed.org/series/TTLHH. (Accessed: Feb. 13, 2024).
[746] See Table HH6 Average Population Per Household and Family: 1940 to Present. Available at: https://www.census.gov/data/tables/time-series/demo/families/households.html. (Accessed: Feb. 13, 2024).
[747] The series contains a unit root (i.e., it is integrated of order one), based on the augmented Dickey-Fuller test.

Figure 4-3: New Light-Duty Vehicle Sales per Household in the United States, 1974–2022



The forecast model includes the natural logarithm of real U.S. GDP and consumer sentiment, as measured by the University of Michigan survey of consumers, as its primary explanatory variables.[748] Because both series are non-stationary as well, their lagged values are also included to ensure stationarity in the residuals. The functional form appears below in Equation 4-1. The model's estimated coefficients and fit to the historical series are described in Table 4-2.

Equation 4-1: Statistical Model Used to Generate Nominal Forecast

$$\begin{aligned} NewVehPerHH_t \\ &= C + \beta_1 NewVehPerHH_{t\text{-}1} + \beta_2 3YrSumPerHH_{t\text{-}1} + \beta_3 LN(GDP_t) \\ &+ \beta_4 LN(GDP_{t\text{-}1}) + \beta_5\ ConsumerSentiment_t + \ \beta_6 ConsumerSentiment_{t\text{-}1} \end{aligned}$$

The signs of all coefficients are consistent with expectations: increases in current GDP and more favorable consumer sentiment both have positive effects on sales, and higher levels of sales in the three previous years suppress those in the current year. The lagged value of the dependent variable, the lagged three-year sum of sales, both GDP variables, and the contemporaneous value of consumer sentiment are all statistically significant, while the lagged consumer sentiment variable is not. Being a time series model, NHTSA must consider the possibility that error terms in the model exhibit serial correlation. The p-value of the Breusch-Godfrey test for serial correlation is (0.67) at order 1, meaning that the agency cannot reject the null hypothesis that there is no first-order serial correlation in the error terms. As a result, the agency concludes that the model is properly specified.

Table 4-2: Summary of Forecast Regression Function

Predictors	Estimates	CI	P
(Intercept)	0.16	0.09 – 0.23	<0.001
$NewVehPerHH_{t\text{-}1}$	0.96	0.77 – 1.16	<0.001
$3YrSumPerHH_{t\text{-}1}$	-0.17	-0.23 – 0.11	<0.001
$LN(GDP_t)$	0.25	0.14 – 0.37	<0.001
$LN(GDP_{t\text{-}1})$	-0.27	-0.38 – -0.16	<0.001

[748] HDPUV sales are defined as the sum of sales in the commercial LTs and light-medium freight trucks as reported in AEO Tables 44 and 49. Upward adjustments were made to the initial growth rates to account for differences.

$ConsumerSentiment_t$	0.0003	0.00003 – 0.0005	0.03
$ConsumerSentiment_{t-1}$	0.00005	-0.0002 – 0.0003	0.74
Observations	47		
R^2 / R^2 adjusted	0.961 / 0.954		

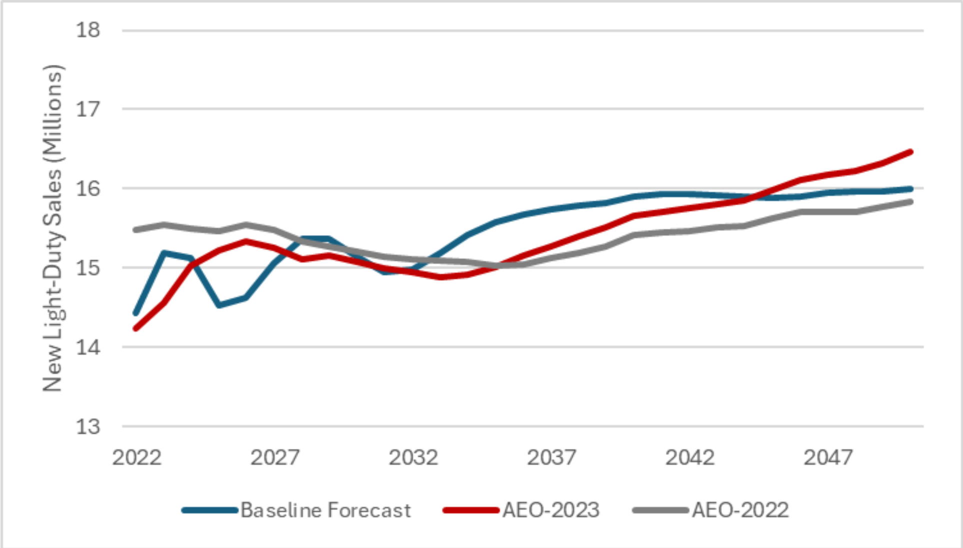
Historical sales totals do not match exactly with sales totals from the compliance data used to create the CAFE Model's 2022 fleet. This difference is likely due to minor differences in vehicle classification and sales reporting. To align the historical sales series used to estimate the econometric sales model with sales quantities in the CAFE Model's analysis fleet, NHTSA adjusted the intercept term in the sales model by the difference in per household sales between the two series in model year 2022. Because the dependent variable is the number of new vehicles sold per household, it is also necessary to multiply its projected value by the number of households to produce an estimate of new vehicle sales for each future year. This model is used to forecast new vehicle sales through 2050, so it is necessary to have projections of each variable used in Equation 4-1 through that year. As indicated previously, NHTSA relies on forecasts of U.S. GDP from the 2023 AEO, and projections of consumer sentiment and number of households from the September 2022 S&P Global Insight March Macroeconomic Outlook. Since the proposed rule was released, data on actual light duty sales for model year 2023 have become available for light-duty vehicles. As a result, NHTSA chose to project sales for the final rule starting in model year 2024 and use actual sales data for model year 2023 light-duty vehicles. Since the CAFE Model's limitations do not allow for us to use a different starting year for its internal sales module, sales are projected using our statistical function outside of the CAFE Model and are provided as a fixed forecast an input found in the Parameters Input File.

While the analysis for light-duty vehicles could have relied on a forecast of new vehicle sales taken from a published source (AEO 2023 as in the case of HDPUV, for example), using a function is an attractive option because it allows the CAFE Model to dynamically adjust the forecast in response to input changes. If a sensitivity case requires a forecast that is consistent with a set of specific (even if unlikely) assumptions, the model can be used to develop a forecast of new vehicle sales consistent with those assumptions, which is unlikely to be available in the public domain. Using a functional form also allows the user to vary some of the assumptions to the analysis without creating inconsistencies with other elements of the analysis, although it is still important to ensure that any set of assumptions is internally consistent.

This function and the set of assumptions contained in the central analysis produces a projection that is comparable in magnitude to the forecast in AEO 2023's Reference Case, but with some important differences. The two forecasts, as well as the AEO 2022 Reference Case forecast which is included for context in Figure 4-4, project new light vehicle sales to grow slightly over the coming decades. However, the reference baseline forecast in this analysis shows some short-term oscillation in sales between the levels seen in the two most recent AEO forecasts before falling below both forecasts in the mid-2020s. This reflects the impact of volatility in the most recent preceding years caused by the COVID-19 pandemic and supply chain disruptions in the new vehicle market. These combined with the projected impact of relatively volatile near-term macroeconomic conditions lead us to project additional fluctuations in the market before levels converge to a similar path as seen in AEO.

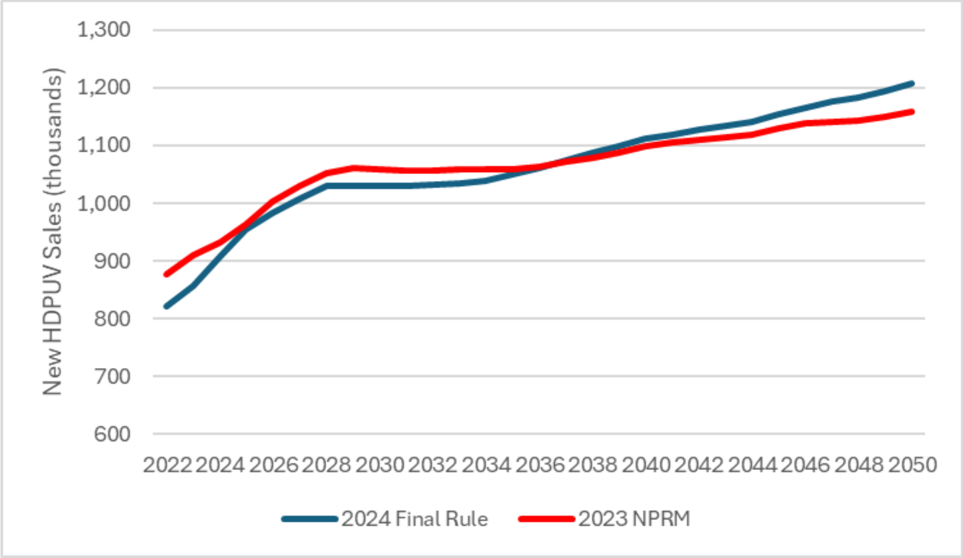
As differences in the AEO 2022 and 2023 forecasts illustrates, the pandemic has created significant uncertainty over the level of projected sales through the 2020s, and using manufacturer compliance data to measure model year 2022 sales introduces an additional divergence with these projections. After the effects of the pandemic recede toward the end of the 2020s, differences among the three forecasts shrink and our forecast follows generally similar trends as the 2023 AEO forecast in later years. Obviously, the economic response to the pandemic has created considerable near-term uncertainty about the pace at which the market for new automobiles will recover—and the scale and timing of the recovery's peak---before returning to its long-term trend.

Figure 4-4: Comparison of Projected New Light-Duty Vehicle Sales with Annual Energy Outlook



As noted earlier, NHTSA decided to use a forecast based on the EIA 2023 AEO forecast for HDPUVs. While this does not allow NHTSA to directly examine the impact of specific changes of various inputs to the forecast, the agency can examine the overall uncertainty in these forecasts over time by examining multiple vintages of the source forecasts. In Figure 4-5, we compare our final rule forecast with the forecast used in the 2023 NPRM. The NPRM forecast was constructed using the 2022 AEO Reference Case forecast. The reference baseline forecast used in the final rule was generated using the same set of assumptions as the NPRM forecast but uses the 2023 AEO Reference Case forecast. We find that our HDPUV forecast is only slightly different from the NPRM, with much of the difference driven by updates to the initial compliance data for the 2022 new vehicle fleet. The overall evolution of sales follows a similar pattern in the later years of the forecast. In general, the earlier vintage is slightly more optimistic during the earlier part of the time range, although the final rule forecast converges to higher levels in the later years.

Figure 4-5: Comparison of Projected HDPUV Vehicle Sales with Prior Forecasts



After forecasting the total number of new vehicle sales in the reference baseline, the CAFE Model applies an estimated price elasticity to determine the change in aggregate new vehicle sales under each regulatory alternative. Price changes for this calculation are based projected regulatory costs for each alternative. NHTSA elected to use a price elasticity of new vehicle demand equal to -0.4 while also considering the effects of uncertainty about its exact value through sensitivity cases. This is the same elasticity used in the 2022 final rule and in the 2023 NPRM. This elasticity is aligned with an EPA report that explored the effects of changes in vehicle prices that arise due to fuel efficiency regulations on vehicle sales and the totality of older research as discussed in detail in our previous rulemaking.[749]

We apply the elasticity to the difference between the alternative's regulatory costs and the sum of the first 2.5 years' worth of fuel savings plus the value of any tax credits that are passed through to the consumer. Since we assume for this analysis that manufacturers will pass the full costs of complying with the standards onto consumers, the regulatory cost is the sum of the cost of technology added to meet the alternative's standards and any fine payments. However, the technology added to meet the standards will increase the consumer's valuation of new vehicles as their increased efficiency will produce fuel savings for their operators. To avoid overestimating the impact of the costs to meet the standards, we must also include an estimate of the resulting change in demand, which is represented in this analysis by the 30-month WTP assumption. For a more complete explanation of the changes in supply and demand caused by the addition of technology that improves fuel economy, see FRIA Chapter 7.1. We assume in our central analysis that the incidence of tax credits is split evenly between consumers and manufacturers. This is discussed in greater detail in Chapter 2.5.2.2 and Preamble Section III.C.5.

The price elasticity is applied to the percent differences in the average selling price of new cars, light trucks, and HDPUVs between the No-Action Alternative and individual regulatory alternatives, in each future year. As discussed in more detail below, these price differences do *not* represent increases or decreases compared to the previous year; instead, they measure the (percent) difference in average prices between the No-Action Alternative and each regulatory alternative. In the No-Action Alternative, the average price is defined as the observed new vehicle price in 2022 (the last historical year before the simulation begins), plus the average regulatory cost necessary for all manufacturers to comply with the standards prevailing in that year. The central analysis for the final rule analysis simulates multiple programs simultaneously (existing CAFE and fuel efficiency standards, existing EPA greenhouse gas standards, ZEV, and the California Framework Agreements), and the regulatory cost includes technology costs, and civil penalties paid for non-compliance (with CAFE standards) in a model year.[750] So the change in sales for alternative *a* in year *y* relative to the reference baseline *b* is:

Equation 4-2: Calculation of Change in Sales

$$\Delta Sales_{y,a} = \frac{(\Delta RegCost_{y,a} - \Delta FuelCosts_{y,a} - \Delta TaxCredits_{y,a})}{MSRP_{2022} + RegCost_{y,b} - TaxCredits_{y,b}} \cdot PriceElasticity \cdot Sales_{y,b}$$

$\Delta RegCost$ is the difference in average regulatory cost between alternative *a* and the reference baseline scenario in year *y* to make a vehicle compliant with the standards, $MRSP_{2022}$ is the average MSRP of a new vehicle in 2022. NHTSA assumes that MSRP represents the average transaction price of new vehicles in its analysis. $Sales_{y,b}$ is the forecasted sales in the reference baseline in year *y*, $\Delta FuelCosts_{y,a}$ is the change in average fuel costs over 2.5 years relative to the reference baseline in year *y*, $\Delta TaxCredits_{y,a}$ is likewise the change in average tax credits passed through to the consumer relative to the reference baseline, and *PriceElasticity* is -0.4.

[749] Jacobsen et al. (2021) report a range of estimates, with a value of approximately -0.4 representing an upper bound of this range. We select this point estimate for the reference baseline and explore alternative values in the sensitivity analysis. Jacobsen, M. et al. 2021. The Effects of New-Vehicle Price Changes on New- and Used-Vehicle Markets and Scrappage. EPA-420-R-21-019. Washington, D.C. Available at: https://cfpub.epa.gov/si/si_public_record_Report.cfm?Lab=OTAQ&dirEntryId=352754. (Accessed: Feb. 13, 2024). The agency previously relied on an elasticity estimate of -1.0, based on a summary report that included a reporting error. Correcting this error no longer supported an elasticity as large in absolute value. For additional detail, see Section III.E.2.a. of the 2022 final rule.
[750] The baseline regulatory costs include all of the costs associated with fuel economy technology assumed to be applied to vehicles in the reference baseline scenario. If a technology is estimated to have a payback period within 30 months, the model will apply it within the reference baseline and that cost would be incorporated into the reference baseline's regulatory cost.

In turn, the change in fuel costs used to adjust price differences for future years under each regulatory alternative is given by Equation 4-3, where 35,000 miles is assumed to be equivalent to 2.5 years of vehicle usage.[751]

Equation 4-3: Change in Fuel Costs Used to Compute Sales Differences

$$\Delta FuelCosts_{y,a} = \left(\frac{FuelPrice_y}{NewVehFE_{y,a}} - \frac{FuelPrice_y}{NewVehFE_{y,b}}\right) * 35000$$

NHTSA assumes that consumers behave as if the fuel price prevailing when they purchase a new car or light truck will be the price they face over the first 2.5 years they own and drive it. Essentially, this means that consumers behave as if fuel prices follow a random walk, where the best prediction of (near) future prices is the price today. Scrappage rates in their first few years of operation are close to zero, so buyers can reasonably expect to travel the full annual mileage in each of the first three years of ownership. Total annual sales under each regulatory alternative will equal those under the reference baseline plus the change caused by that alternative; expressed in terms of the equations above, $Sales_{y,b} + \Delta Sales_{y,a}$ for alternative *a* in year *y*. This implementation produces total sales estimates that vary among alternatives and over time. The estimated effects on sales of the various alternatives considered here are discussed in detail in the accompanying FRIA Chapters 8.2.2 and 8.3.2.

4.2.1.3. Modeling Changes in Fleet Mix

The first two modules described above (the nominal sales forecast and price elasticity) determine total industry sales in each year from 2023 to 2050 under each alternative considered.[752] A third module, the fleet share module, distributes total industry light-duty sales between two different body-types: "cars" and "light trucks."

As part of the 2022 final rulemaking process, NHTSA examined multiple approaches to projecting reference baseline fleet share using mathematical functions. The two primary options were (i) a specification from the transportation module of the NEMS, and (ii) an alternative econometric model developed by agency staff and outlined in a docket memo titled "Exploration of alternate fleet share module."[753] Ultimately, NHTSA decided to use the NEMS model for its central analysis in the previous rulemaking and continued to explore alternatives for the 2023 proposal.

Models like those NHTSA examined during the proposal can be sensitive to projected changes in their inputs over time and there is wide uncertainty in their future values. The agency decided during the proposal that projections from an authoritative outside source were likely to be more reliable than those produced by the candidate approaches it tested. NHTSA followed this same approach for the final rule. Thus, the fleet share module in this final rule relies on share projections derived from the agency's own compliance data for the 2022 fleet, and the 2023 AEO projections for later years.[754] To reconcile differences in the initial 2022 shares, NHTSA projected the fleet share forward using the annual changes from 2022 predicted by AEO and applied these to the agency's own compliance fleet shares for model year 2022. These projected fleet shares can be found in the Parameters Input File.

These shares are then applied to the total industry light-duty sales projected in the first stage of the sales analysis to produce total industry volumes of car and light truck body styles. Individual model sales are then determined by multiplying individual manufacturers' shares of each body style (either car or light truck) by total industry sales of that body style, and then assuming that each model within that body style a manufacturer retains the same fraction of those sales as in model year 2022. This process implicitly assumes that

[751] Based on odometer data, 35,000 miles is a good representation of typical new vehicle usage in the first 2.5 years of ownership and use—though the distribution of usage is large.
[752] Sales for model year 2022 are based on totals from certified compliance data.
[753] See NHTSA-2021-0053-0010.
[754] See 2023 AEO Table 38 Light-Duty Vehicle Sales by Technology Type. Available at: https://www.eia.gov/outlooks/aeo/data/browser/#/?id=48-AEO2023&cases=ref2023&sourcekey=0. (Accessed: Feb. 13, 2024).

consumer preferences for particular styles of vehicles are determined in the aggregate (at the industry level), but that manufacturers' market share of those body styles remain at model year 2022 levels.

Within a given body style, each manufacturer's shares of individual models are also assumed to be constant over time. This approach implicitly assumes that manufacturers are currently pricing individual vehicle models within the market segments where they compete in a way that maximizes their profit. Without more information about each OEM's true cost of production and operation, fixed and variables costs, and profit margins on individual vehicle models, the agency has no basis to assume that strategic shifts within a manufacturer's portfolio will occur in response to standards.

The fleet share projection used by NHTSA predicts a long-term decline in passenger cars as a share of the light-duty fleet. Between 2022 and 2050, the agency assumes in the reference baseline that passenger cars will decline as a share of the fleet from just under 40 percent to about 30 percent. This represents a continuation of long-term trends, as the share of passenger cars in US light-duty vehicle production has declined to less than half its pre-CAFE value in 1975.[755] This trend is likely the result of numerous market effects including changes in consumer preferences, the designs and features of light trucks and passenger cars, their relative fuel economies, and differences in vehicle production costs.

The forecast from the 2023 AEO captures long-term trends in fleet share but does not provide estimates of changing fleet mix across the regulatory alternatives. To capture changes across alternatives, the fleet share module tracks price changes due to technology application and applies a fleet share adjustment based on the evolving relative price difference between cars and light trucks. This price change is computed net of the present value of fuel savings and the consumer's share of any tax credits. The CAFE Model employs a calibrated binomial logit model of car and light truck market shares as the foundation for the fleet share adjustment across regulatory alternatives. The share adjustment used for this calculation is derived from a review of the published literature and was calibrated based on estimates of own-price elasticities from the economics literature. The agency describes this literature review and the calibrated logit model in more detail in the accompanying docket memo "Calibrated Estimates for Projecting Light-Duty Fleet Share in the CAFE Model."

As a result of this review, NHTSA selected a price coefficient of -0.000042, which enters the linear utility function of consumers and determines their average preferences between cars and light trucks. The coefficient price, which we denote as β, is equal in magnitude to the marginal utility of a dollar in present value terms, or the marginal utility that spending an additional dollar of income provides. This can then be thought of as the utility loss that the consumer experiences when prices for vehicles increase. Because the decision makers in the aggregate model are assumed to consist of all consumers, the same coefficient of price applies in the car and truck utility functions. The CAFE Model uses this coefficient, the reference baseline market shares of passenger cars and trucks, along with the incremental regulatory costs net of fuel savings and tax credits for each vehicle class to predict the incremental effect of a regulatory alternative on fleet share in each year based on Equation 4-4.

Equation 4-4: Parameterized Fleet Shares in Each Regulatory Alternative

$$s_{Tti}=\frac{1}{1+e^{K_{Ct0}-K_{Tt0}+\beta(D_{Cti}-D_{Tti})}} \quad \text{and} \quad s_{Cti}=\frac{1}{1+e^{K_{Tt0}-K_{Ct0}+\beta(D_{Tti}-D_{Cti})}}$$

In this formulation, s_{Tti} and s_{Cti} represent the fleet shares of light trucks and passenger cars respectively in year t in regulatory alternative i. D_{Ctm} and D_{Ttm} represent the differences between the incremental changes in the sum of each vehicle type's prices, the present value of fuel costs, and the value of tax credits passed through to consumers. The price measure is assumed to change in proportion of regulatory costs under each alternative. The fuel cost measure represents savings over the first 30 months of vehicle ownership. Each of these changes is measured for a specific regulatory alternative relative to the reference baseline. K_{Ct0} and K_{Tt0} are constants from the No-Action alternative such that:

[755] EPA. 2022. The 2022 EPA Automotive Trends Report, Greenhouse Gas Emissions, Fuel Economy, and Technology since 1975: Executive Summary. EPA-420-R-22-029. Available at: https://www.epa.gov/system/files/documents/2022-12/420r22029.pdf. (Accessed: Apr. 1, 2024).

Equation 4-5: Parameterized Reference Baseline Constants

$$K_{Ct0}\text{-}K_{Tt0}=ln\left(\frac{1}{s_{Tt0}}-1\right) \quad \text{and} \quad K_{Tt0}\text{-}K_{Ct0}=ln\left(\frac{1}{s_{Ct0}}-1\right).$$

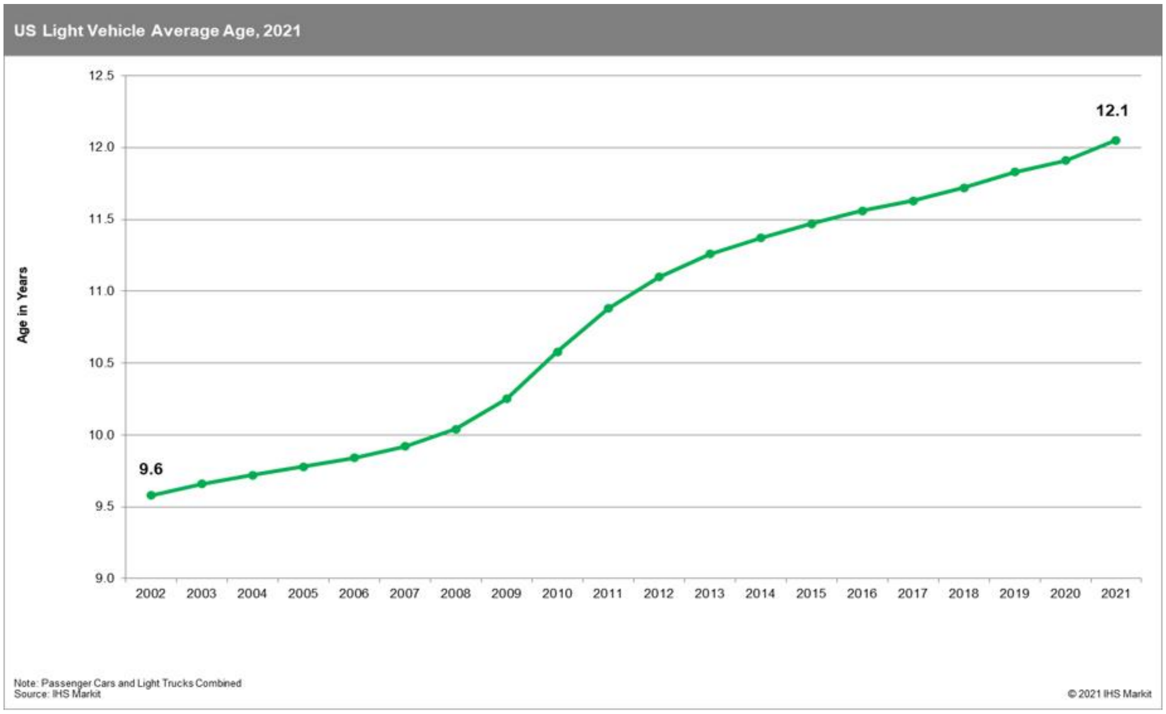
The car share is $1 - S_{Tti}$ and vice versa, ensuring that their market shares in each alternative, at each time period, sum to 1. Intuitively, β equals the percentage change in the ratio of cars to trucks that results from an increase in the price of cars relative to trucks. So if changes to the CAFE Standards cause truck prices to increase by $1,000 more than they cause the price of cars to increase in a regulatory alternative, then the ratio of cars to trucks should increase proportionately by 4.2 percent of the reference baseline ratio.

4.2.2. Modeling Changes in Vehicle Retirement Rates

The effects of this rulemaking on the fuel economy, prices, and other features of new cars, light trucks, and HDPUVs will affect not only their sales, but also the demand for used vehicles. This is because used vehicles—especially those produced more recently—are a close substitute for new models, so changes in prices and other attributes of new cars and light trucks will affect demand for used models. In turn, this will affect their market value as well as the number of used vehicles remaining in service.

Changes in the number of used vehicles in service, and by extension how much they are driven, have important consequences for fuel consumption, emissions of CO_2 and criteria air pollutants, and safety. The average age of a registered light-duty vehicle in the United States has already risen by more than 40 percent since 1995, and topped 12 years old for the first time in 2021 (see Figure 4-6, from IHS Markit).[756] In light of this trend, it is important to capture the changes to vehicle usage and retirement in the used market that may be caused by regulation of the new vehicle market.

Figure 4-6: Average Age of a Registered Light-Duty Vehicle in United States



This subchapter discusses the basis for the scrappage effect of higher CAFE standards and higher fuel efficiency standards for HDPUVs, traces each of these effects in detail, and explains how the magnitude of this effect is estimated for this action. Like many of the effects estimated in this analysis, the magnitude of the simulated standards' effect on scrappage rates is subject to uncertainty. As a consequence of our

756 S&P Global Mobility. 2021. Average Age of Cars and Light Trucks in the US Rises to 12.1 Years, Accelerated By COVID-19. Available at: https://news.ihsmarkit.com/prviewer/release_only/id/4759502/. (Accessed: May 31, 2023).

assumptions about how consumers value fuel economy and fuel efficiency, and when manufacturers will voluntarily adopt technology, the direction of the scrappage effect is unambiguous even though the magnitude is less certain. For this final rule, NHTSA models scrappage for HDPUVs using the light truck scrappage model parameters. This fleet is primarily made up of pickup trucks and scrappage decisions for these vehicles are expected to most closely mirror those of other trucks in the light-duty market.

4.2.2.1. Foundation of the Scrappage Effect

Fuel economy and efficiency standards increase the cost of acquiring new vehicles, but also improve the quality of those vehicles by increasing their fuel economy. The CAFE Model assumes that consumers value the first 30 months of fuel savings at the time of purchase, so that the quality-adjusted change in new vehicle prices is the increase in regulatory costs minus 30 months of fuel savings. Because the CAFE Model also assumes that in the No-Action Alternative manufacturers will adopt fuel economy and fuel efficiency technologies with a payback period of 30 months or less, it follows that there will be net price increases in any regulatory scenario. Higher standards make it costlier for manufacturers to produce vehicles and, as a result, prices of new vehicles increase. As long as the quality-adjusted price increases,[757] sales of new vehicles are likely to decline, on the margin. Through the lens of supply and demand curve interactions, the quality-adjusted price increase equates to a shift inward of the supply curve for new vehicles. All else equal, this movement corresponds to an increase in the equilibrium price, and decrease in equilibrium quantity, of new vehicles purchased.

New and used vehicles are substitutes. When the price of a good's substitute increases, the demand curve for that good shifts outward and the equilibrium price and quantity supplied both increase. Thus, increasing the quality-adjusted price of new vehicles will result in an increase in equilibrium price and quantity of used vehicles. Since, by definition, used vehicles are not being "produced" but rather "supplied" from the existing fleet, the increase in quantity must come via a reduction in their retirement rates. Practically, when new vehicles become more expensive, demand for used vehicles increases (and these used vehicles become more expensive). Because used vehicles are more valuable in such circumstances, they are scrapped at a lower rate, and just as rising new vehicle prices push marginal prospective buyers into the used vehicle market, rising used vehicle prices force marginal prospective buyers of used vehicles to acquire older vehicles or vehicles with fewer desired attributes.

See FRIA Chapter 7.1 for a more detailed theoretical discussion of the effects of higher standards on the used vehicle market.

4.2.2.2. Model Development

An unintended consequence of emissions standards on scrappage rates was first observed by Gruenspecht shortly after the inaugural CAFE standards were promulgated in 1978.[758] Gruenspecht identified criteria pollutant standards as a form of differentiated regulation; a regulation that affected some vehicles but not others – in this case, new vehicles but not used vehicles. CAFE standards are another form of differentiated regulation, regulating the fuel economy of new, but not used, vehicles and so may produce the same kind of scrappage effect in the used vehicle population. Since then, the relationship between fuel economy standards and scrappage has been a growing topic of academic literature. In preparation of the model years 2021-2026 rule—which marked the first CAFE rulemaking to dynamically model scrappage—the agency performed a detailed review of the literature on this topic.[759] The principal conclusion from the literature review was that, among the studies that have attempted to estimate this effect directly, there is consensus about both its existence and direction (i.e., higher used vehicle prices lead to slower retirement rates) but estimates of the magnitude of the effect vary. The agency used the literature and other regulatory scrappage

[757] The quality adjusted price is considered higher when regulatory compliance costs exceed 30 months of fuel savings.
[758] Gruenspecht, H. 1982. Differentiated Regulation: The Case of Auto Emissions Standards. *American Economic Review*. Vol. 72(2): pp. 328–31. Available at: https://econpapers.repec.org/article/aeaaecrev/v_3a72_3ay_3a1982_3ai_3a2_3ap_3a328-31.htm. (Accessed: Apr. 1, 2024).
[759] *See* 83 FR 43093-94 (Aug. 24, 2018).

models—mainly CARB's 2004 CARBITS vehicle transaction choice model[760]—as a springboard to create a scrappage model that would be internally consistent with the broader CAFE Model.[761]

While the agency did not use any particular model from the literature, the agency retained the framework outlined by Greenspan and Cohen to construct the CAFE Model's scrappage model. Greenspan and Cohen identified two types of scrappage: engineering and cyclical scrappage.[762] Engineering scrappage represents the physical wear on vehicles which results in their being scrapped. Cyclical scrappage represents the effects of macroeconomic conditions on the relative value of new and used vehicles—under economic growth the demand for new vehicles increases and the value of used vehicles declines, resulting in increased scrappage and more rapid fleet turnover.

In addition to allowing new vehicle prices to affect cyclical vehicle scrappage à la the Gruenspecht effect, Greenspan and Cohen also note that engineering scrappage seemed to increase when EPA criteria pollutant emissions standards became more stringent; as more costs went towards compliance technologies, scrappage increased. In this way, Greenspan and Cohen theorize two ways that fuel economy and fuel efficiency standards could affect vehicle scrappage: 1) through increasing new vehicle prices, thereby increasing used vehicle prices, and finally, reducing on-road vehicle scrappage, and 2) by shifting resources towards fuel-saving technologies—potentially reducing the durability of new vehicles.[763]

Under this framework, standards directly influence engineering scrappage, and influence cyclical scrappage through their effect on the relative prices of new vehicles. However, macroeconomic conditions including GDP and fuel prices are assumed to evolve exogenously. The current implementation of the scrappage model is relatively unchanged from the scrappage model used in the 2020 final rule, which had made a variety of improvements as compared to the model used for the prior NPRM and addressed other substantive comments. The same model was used for the 2021 proposal, 2022 final rule, and 2023 proposal.

4.2.2.2.1. Variables and Data Used to Estimate Scrappage

Many competing factors influence the decision to scrap a vehicle, including the cost to maintain and operate it, a household's demand for VMT, the cost of alternative means of transportation, and the value that could be attained through reselling or scrapping the vehicle for parts. An owner will decide to scrap a vehicle when the value of the vehicle is less than the value of the vehicle as scrap metal, plus the cost to maintain or repair the vehicle. In other words, the owner gets more value from scrapping the vehicle than continuing to drive it, or from selling it. Typically, the owner that scraps the vehicle is not the first owner. For the purposes of this exercise, any vehicle that disappears from the U.S. population is considered to be retired or "scrapped," despite the fact that many of them are neither dismantled nor actually retired from service. Many vehicles, whose value has declined to a point where continuing to operate and maintain them in the United States no longer makes economic sense, are merely exported to other countries (typically sold at auction) where they continue their lives for some number of years. Others disappear as a result of collisions or irreparable mechanical failures but present in the same way for our purposes here – they fail to appear in the registration roles and, for our purposes, are assumed to be scrapped.

While scrappage decisions are made at the owner level, the agency is unaware of sufficient household data to capture scrappage at that level. Instead, NHTSA uses aggregate data measures that capture broader market behavior.

The agency is interested in how changes in new vehicle prices and fuel economy affect the retirement rate of the on-road fleet *over time.* In order to isolate this effect, NHTSA needed multi-period data on the scrappage rates of used vehicles and prices of new vehicles. Scrappage, itself, is a phenomenon inherently defined over multiple time periods; it represents a change in a vehicle (or model year cohort's) registration status between one period and the next. As such, the potential scrappage effect can only be measured through time series

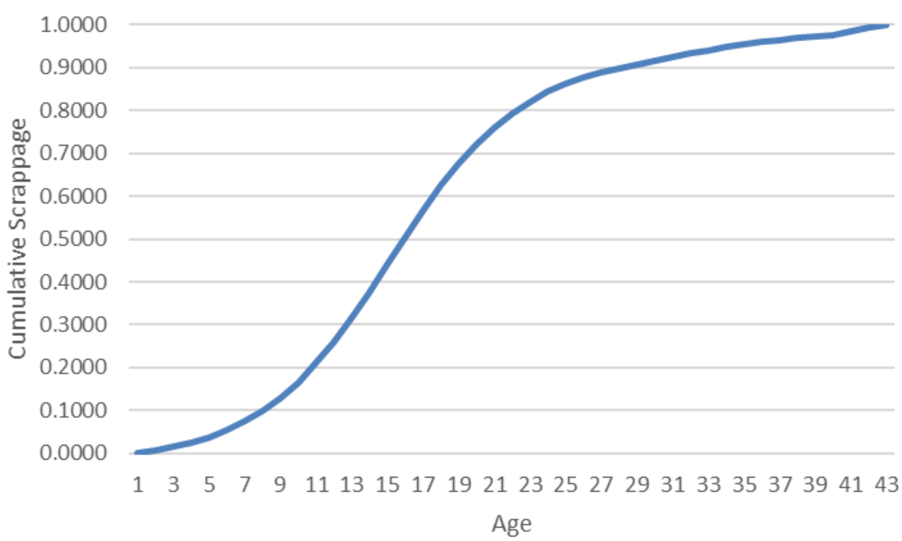
[760] *Id.*
[761] There were four elements identified as being necessary. The agency noted that none of the existing scrappage models in literature met all four criteria.
[762] Greenspan, A., Cohen, D. 1999. Motor Vehicle Stocks, Scrappage, and Sales. *Review of Economics and Statistics*. Vol. 81(3): pp. 369–83. Available at: https://doi.org/10.1162/003465399558300. (Accessed: Apr. 1, 2024).
[763] Note that the authors posit a relationship between durabilty and emission stanadards; NHTSA does not itself have data indicating a reduction in durability.

data. The data contain information about national vehicle registrations in each calendar year from 1975 to 2017.[764]

4.2.2.2.1.1. Age and Durability

The most predictive element of vehicle's scrappage in a given year is the influence of 'engineering scrappage.' This source of scrappage is largely determined by the age of a vehicle and the durability of a specific model year vintage. For a model year cohort, vehicle scrappage typically follows a roughly logistic function with age—that is, instantaneous scrappage increases to some peak, and then declines, with vehicle age until all (or nearly all) of the vehicles produced in a given year have been retired (which is illustrated in Figure 4-7).

Figure 4-7: Cumulative Scrappage for a Model Year Cohort



NHTSA uses proprietary vehicle registration data from IHS-Polk, the National Vehicle Population Profile (NVPP),[765] to collect vehicle age and estimate durability. While the agency gives preference to publicly accessible data whenever possible, the NVPP represents the most comprehensive and complete source of vehicle registration information the agency has identified to date.

Polk separates registered vehicles into finer market segments based on body style and gross vehicle weight rating. In order to build scrappage models to support this action, it was important to aggregate these vehicle types in a way that is compatible with the existing CAFE Model.

Since for the purposes of this analysis, vans/SUVs are sometimes classified as passenger cars and sometimes as light trucks for regulatory purposes, survival schedules were developed to vary by body style. Separate models were developed for cars, vans/SUVs, and pickup trucks. This approach is preferable to alternative methods—such as dividing vehicles by regulatory class—because VMT schedules are calculated based on body style in the analysis. Furthermore, these vehicle body styles are assumed to serve different purposes and, as a consequence, likely result in different lifetime scrappage patterns.

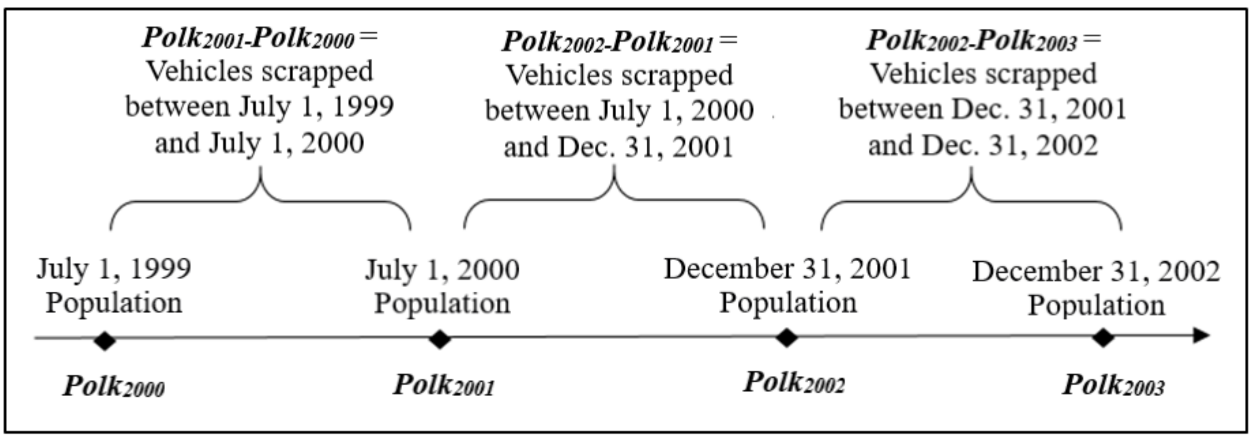
Once stratified into body style buckets, the data are aggregated into population counts by vintage (model year) and age. These counts represent the population of vehicles of a given body style and vintage in a given calendar year. The number of vehicles remaining in the fleet can be viewed as a measure of the durability of a particular model. The difference between the counts of a given vintage and body style from one calendar year to the next is assumed to represent the number of vehicles of that vintage and style scrapped in a given year.

[764] The analysis begins in 1975 as this is the earliest year all required input data were available.
[765] Includes content supplied by IHS Markit: Copyright © R.L. Polk & Co., 2018. All rights reserved.

One issue with using snapshots of registration databases as the basis for computing scrappage rates is that vehicles are not removed from registration databases until the last valid registration expires. For example, if registrations are valid for a year, vehicles will still appear to be registered in the calendar year in which they are scrapped. To correct for the scrappage that occurs during a calendar year, a similar correction as that in Greenspan and Cohen (1999) is applied to the Polk registration data. We assume that the real on-road count of vehicles of a given model year registered in a given calendar year (CY) is best represented by the Polk count of the vehicles of that model year in the succeeding calendar year ($Polk_{CY+1}$). For example, the vehicles scrapped between calendar year 2000 and calendar year 2001 will still remain in the Polk snapshot from calendar year 2000 ($Polk_{CY2000}$), as they will have been registered at some point in that calendar year, and therefore exist in the database. Using a simplifying assumption that all States have annual registration requirements,[766] vehicles scrapped between July 1st, 1999 and July 1st, 2000 will not have renewed registration between July 1st, 2000 and July 1st, 2001, and will not show up in $Polk_{CY2001}$. The vehicles scrapped during CY2000 are therefore represented by the difference in count from the CY 2000 and CY 2001 Polk datasets: $Polk_{CY2001}$ - $Polk_{CY2000}$.

For new vehicles (vehicles where model year is greater than or equal to calendar year), the count of vehicles will be smaller than the count in the following year—not all of the model year cohort will have been sold and registered. For these new model years, Greenspan and Cohen assume that the Polk counts will capture all vehicles that were present in the given calendar year and that approximately one percent of those vehicles will be scrapped during the year. Importantly, this analysis begins modeling the scrappage of a given model year cohort in: *CY=MY+2*,[767] so that the adjustment to new vehicles is not relevant in the modeling because it only considers scrappage after the point where the on-road count of a given model year vintage has reached its maximum.

Figure 4-8: Visualization of Greenspan-Cohen Adjustment and Polk Data Collection Change



There is a discontinuity between 2001 and 2002 data due a change in data collection.[768] Scrappage computed for calendar year 2001 represents the difference between the vehicle count reported in $Polk_{CY2002}$ and $Polk_{CY2001}$. $Polk_{CY2001}$ represents all vehicles on the road as of July 1st, 2000, and $Polk_{CY2002}$ represents all vehicles on the road as of December 31, 2001. For this one timespan, the scrappage will represent vehicles scrapped over a 17-month time period, rather than a year. For this reason, the calendar year 2001

[766] In future analysis, it may be possible to work with State-level information and incorporate State-specific registration requirements in the calculation of scrappage, but this correction is beyond the initial scope of this rulemaking analysis. Such an approach would be extraordinarily complicated as States can have very different registration schemes, and, further, the approach would also require estimates of the interstate and international migration of registered vehicles.

[767] Calculating scrappage could begin at CY=MY+1, as for most model year the vast majority of the fleet will have been sold by July 1st of the succeeding CY, but for some exceptional model years, the maximum count of vehicles for a vintage in the Polk data set occurs at age two.

[768] Prior to calendar year 2002, Polk vehicle registration data were collected as a single snapshot on July 1st of every calendar year. For calendar years 2002 and later, Polk changed the timing of the data collection process to a rolling collection ending on December 31. That is, they consider information from other data sources to remove vehicles from the database that have been totaled in crashes before December 31st, but may still be active in State registration records. The switch to a partially rolling dataset means that some of the vehicles scrapped in a calendar year will not appear in the dataset and their scrappage will wrongly be attributed to the year prior to when the vehicle is scrapped. While this is less than ideal, these records represent only some of the vehicles scrapped during crashes and scrappage rates due to crashes should be relatively constant over the 2001 to 2002-time period. For these reasons, NHTSA expects the potential bias from the switch to a partially rolling dataset to be limited. Thus, the Greenspan and Cohen adjustment applied does not change for the dataset complied from Polk's new collection procedures.

scrappage data point is dropped, and because of the difference in the time period of vehicles scrapped under the old and new collection schemes, an indicator for scrappage measured before and after calendar year 2001 was considered; however, this indicator is not statistically significant, and is dropped from the preferred model. Variations in the resolution of state registration data over time have caused some calendar years to contain a larger number of vintages than others – the trend being that the oldest calendar years contain the fewest ages. The number of observations for each range of vehicle ages (across the set of calendar year snapshots) is summarized in Table 4-3.

Table 4-3: Summary Vehicle Age and Vintage

Ages	Calendar Years	Count
0-15	1975-2017	43
16	1994-2017	24
17	1995-2017	23
18	1996-2017	22
19	1997-2017	21
20	1998-2017	20
21	1999-2017	19
22	2000-2017	18
23	2001-2017	17
24	2001-2017	17
25	2001-2017	17
26	2001-2017	17
27-39	2001-2017	17

4.2.2.2.1.2. New Vehicle Prices

As discussed earlier, new and used vehicles are substitutes. Therefore, the price of new vehicles will have a strong effect on the value of used vehicles and, thus, their scrappage rates. This is the primary mechanism by which higher standards affect retirement rates of used vehicles. For historical data on new vehicle transaction prices, NHTSA uses data from the National Automobile Dealers Association (NADA).[769] The transaction prices are the average amount consumers paid for new vehicles and exclude any trade-in value credited towards the purchase. The econometric model used to derive coefficients for the CAFE Model's scrappage module uses year-to-year variation in these prices. This price series will capture market-wide patterns in vehicle price changes; however, since the transaction prices are not broken-down by body style, the model may miss unique trends within a particular vehicle body style. This may be particularly relevant for vehicles such as pickup trucks and HDPUVs, which have experienced considerable changes in average price as luxury and high-end options have entered the market over the past decade.

NHTSA considered using the Bureau of Labor Statistics (BLS) New Vehicle Consumer Price Index (CPI). The purpose of BLS data is to show how prices of similar goods and services change over time. As such, the BLS New Vehicle CPI adjusts prices based on vehicle features—such as safety and fuel economy improvements. While this is good for some purposes, it incorporates into the price assumptions that are controlled for elsewhere in this analysis.

[769] The data can be obtained from NADA. For reference, the data for model year 2020 may be found at https://www.nada.org/nadadata/.

As further justification, Parks (1977) cites a discontinuity found in the amount of quality adjustments made to the series so that more adjustments are made over time.[770] This could further limit the ability for the BLS New Vehicle CPI to predict changes in vehicle scrappage.

To ensure consistency with the sales response mechanism in the CAFE Model, the observed transaction prices have been modified for estimation (and subsequent simulation inside the CAFE Model). In the tables that follow, *New Price - FS* represents the average price of new vehicles minus 30 months of fuel savings for all body styles. The final specification treats the coefficient on the age interactions for this term as zero for all body styles, but alternative specifications were tested that allow the elasticity of scrappage to vary with age.

4.2.2.2.1.3. Fuel Prices, Fuel Economy, and Cost Per Mile

Instantaneous vehicle scrappage rates are also influenced by fuel economy, fuel efficiency and fuel prices. Historical data on the fuel economy by vehicle style from model years 1979-2016 were obtained from the 2016 EPA Fuel Economy Trends Report.[771] The van/SUV fuel economy values represent a sales-weighted harmonic average of the individual body styles. Fuel prices were obtained from Department of Energy (DOE) historical values, and future fuel prices within the CAFE Model use the AEO 2023 Reference Case fuel price projections.[772] Fuel price assumptions in this analysis are described further in Chapter 4.1.2. From these values the average cost per 100 miles of travel for the cohort of new vehicles in a given calendar year and the average cost per 100 miles of travel for each used model year cohort in that same calendar year are computed.[773] The agency expects that as the new vehicle fleet becomes more efficient (holding all other attributes constant), it will be more desirable, and the demand for used vehicles should decrease (increasing their scrappage). As a given model year cohort becomes more expensive to operate due to increases in fuel prices, it is expected the scrappage rate of vehicles from that model year will increase. It is perhaps worth noting that more efficient model year vintages will be less susceptible to changes in fuel prices, as absolute changes in their cost per mile (CPM) will be smaller. The functional forms of the cost per mile measures are further discussed in the model specification subchapter below.

4.2.2.2.1.4. Macroeconomic Data

To capture the cyclical effects of scrappage, the model must include a variable accounting for economic conditions. The agency uses the growth rate of real GDP for the analysis. GDP growth rates are sourced from the 2023 AEO reference forecast for the years 2022 through 2050 and extrapolated at the final (stable) growth rate through 2090. Because the purpose of building this scrappage model is to project vehicle survival rates under different fuel economy alternatives, and the current fuel economy projections go as far forward as calendar year 2050, using a data set that encompasses projections at least through 2050 is essential.

NHTSA considered using U.S. unemployment rate and per capita personal disposable income as alternatives to GDP growth rate to capture the cyclical component of the macro-economy. Since these three variables are highly correlated, the model may only contain one of these indicators. The agency tested the scrappage model with unemployment and per capita personal disposable income data, gathered from the Bureau of Economic Analysis (BEA). The results showed evidence of autocorrelation in the error terms that is absent when GDP is used instead.

[770] Parks, R. W. 1977. Determinants of Scrapping Rates for Postwar Vintage Automobiles. *Econometrica*. Vol. 45(5): p. 1099. Available at: https://www.jstor.org/stable/1914061. (Accessed: May 31, 2023).
[771] EPA. 2016. Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends - 1975 through 2016. EPA-420-R-16-010. Available at: https://19january2017snapshot.epa.gov/sites/production/files/2016-11/documents/420s16001.pdf. (Accessed: Feb. 13, 2024).
[772] Note: The central analysis uses the AEO reference fuel price case, but sensitivity analysis also considers the possibility of AEO's low and high fuel price cases.
[773] Work by Jacobsen and van Bentham (2015) suggests that these initial average fuel economy values may not represent the average fuel economy of a model year cohort as it ages — mainly, they find that the most fuel-efficient vehicles scrap earlier than the least fuel-efficient models in a given cohort. This may be an important consideration in future endeavors that work to link fuel economy, VMT, and scrappage. Studies on "the rebound effect" suggest that lowering the fuel cost per driven mile increases the demand for VMT. With more miles, a vehicle will be worth less as its perceived remaining life will be shorter; this will result in the vehicle being more likely to be scrapped. A rebound effect is included in this analysis, but expected lifetime VMT is not included within the current dynamic scrappage model. Jacobsen, M., van Benthem, A. 2015. Vehicle Scrappage and Gasoline Policy. *American Economic Review*, 105 (3): pp. 1312-38. Available at: https://www.aeaweb.org/articles?id=10.1257/aer.20130935. (Accessed: Feb. 13, 2024).

4.2.2.2.1.5. Cash for Clunkers

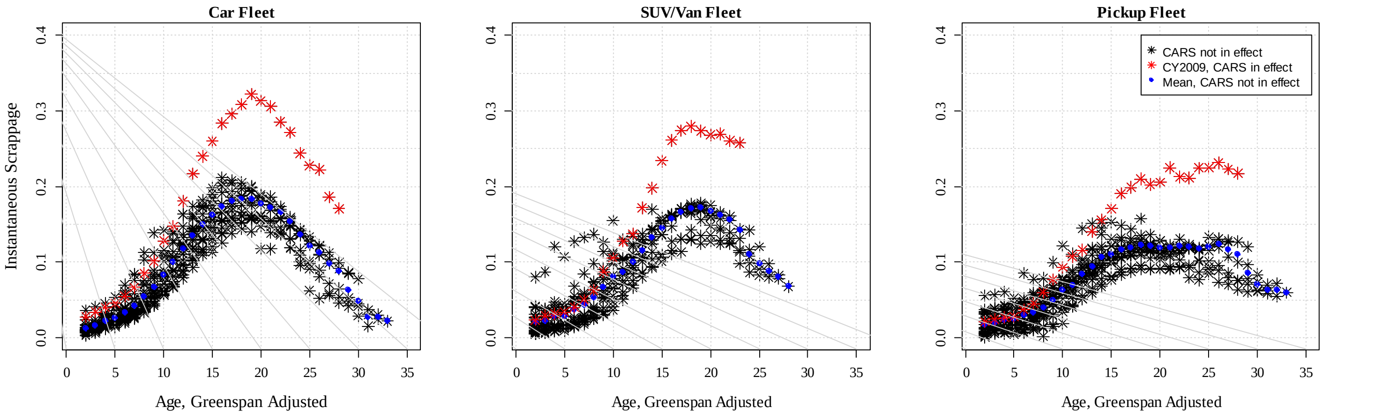
On June 14, 2009, the Car Allowance Rebate System (CARS) became law, with the intent to stimulate the economy through automobile sales and accelerate the retirement of older, less fuel efficient and less safe vehicles. The program offered a $3,500 to $4,500 rebate for vehicles traded-in for the purchase of a new vehicle. Vehicles were subject to several program eligibility criteria: first, the vehicle had to be drivable and continuously registered and insured by the same owner for at least one year; second, the vehicle had to be less than 25 years old; third, the MSRP had to be less than $45,000; and finally, the new vehicle purchased had to be more efficient than the trade-in vehicle by a specified margin. The fuel economy improvement requirements by body style for specific rebates are presented in Table 4-4.

Table 4-4: CARS Fuel Economy Improvement Required for Rebates by Regulatory Class

	$3,500 Rebate Eligibility	$4,500 Rebate Eligibility
Passenger Car	4-9 MPG Improvement	10+ MPG Improvement
Light Truck	2-5 MPG Improvement	5+ MPG Improvement

By August 25, 2009, the program spent its $2.85 billion budget on 678,359 eligible transactions. As a condition of the program, the vehicles were scrapped at the point of trade-in by destroying the engine. The CARS program arguably had two transitory effects on scrappage. First, some vehicles may have been prematurely scrapped in exchange for the trade-in credit. Second, the trade-in incentive likely increased demand for new vehicles, which in-turn increased new vehicle prices. Both of these effects would accelerate scrappage for the duration of the program. The Polk data support this hypothesis as vehicle scrappage rates spiked in 2009. Figure 4-9 shows the impact of the program from another perspective. It shows the observed instantaneous scrappage rate of model years 1977-2015 by age for calendar years 1980-2015. The black stars represent observed scrappage rates for calendar years where the CARS program was not in effect, the red stars represent calendar year 2009 when the CARS program was in effect, and the blue dots represent the mean value of the scrappage when CARS was not in effect.

Figure 4-9: Impacts of the 2009 CARS by Body Style



Li, Linn, and Spiller (2013) used Canada as a counterfactual example to identify the portion of CARS trade-ins attributable to the policy, i.e., trade-ins that would not have happened anywhere if the program were not in place.[774] They argued that the Canadian market is largely similar to the U.S. market, in part based upon the fact that 13 to 14 percent of households purchased new vehicles one year pre-recession in both countries.

[774] Li, S. et al. 2013. Evaluating Cash-for-Clunkers - Program Effects on Auto Sales and the Environment. *Journal of Environmental Economics and Management.* Vol. 65(2): pp. 175–93. Available at: https://doi.org/10.1016/j.jeem.2012.07.004.. (Accessed: Feb. 14, 2024).

They also argued that the economic crisis affected the Canadian economy in a similar manner as it affected the U.S. economy. They noted that when Canada offered a small rebate of $300 to vehicles traded in during January 2009, only 60,000 vehicles were traded in under that program. Using those assumptions, Li, et al., applied a difference-in-difference methodology to isolate the effect of the CARS program on the scrappage of eligible vehicles. Li, et al., found a significant increase in the scrappage only for eligible U.S. vehicles, suggesting they isolated the effect of the policy. They conclude that of the 678,359 trade-ins made under the program, 370,000 of those would not have happened during July and August 2009.

The agency finds the evidence from Li, et al. (2013), persuasive toward the inclusion of a control for the CARS program during calendar year 2009. Notable from Table 4-8 is that the effect of CARS on instantaneous scrappage is largest around the point that the average scrappage peaks for all other calendar years for each body style. For cars the effect of the program increases until around age 20 and then decreases, for vans/SUVs the effect increases until just after age 15 and then decreases at a much slower rate, and finally, for trucks the effect increases steadily until around age 17 and then nearly levels off for all observed ages. For this reason, a dummy variable for calendar year 2009 was interacted with linear and non-linear age variables to represent the effect of the CARS program. The analysis confirmed that modeling as a constant dummy variable is sufficient to capture the nonlinear effect and accurately predict the spikes in scrappage under the CARS program.

4.2.2.3. Model Specification

4.2.2.3.1. Stationarity Testing

As discussed earlier, the scrappage model utilizes panel data, which combine repeated observations on multiple individuals or cohorts over time. The data employed by the scrappage model observes the scrappage rates of individual model year cohorts between successive calendar years. The model allows for the isolation of trends over time and across individuals.[775] Since the scrappage model uses aggregate model year cohorts to estimate scrappage rates by age and time-dependent variables (new vehicle prices, fuel prices, GDP growth rate, etc.), panel data are necessary to estimate the model. A major challenge to using panel data is that the data structure requires consideration of potential violations of econometric assumptions necessary for consistent and unbiased estimates of coefficients both across the cross section and along the time dimension. The cross section of the scrappage data introduces potential heterogeneity bias—where model year cohorts may have cohort-specific scrappage patterns.[776] Stated differently, each model year may have its own inherent durability. The time dimension of a panel introduces a set of potential econometric concerns present in time series analysis.

Before devising the scrappage model, the agency needs to determine which, if any, of the variables are non-stationary. The agency uses the Augmented Dickey-Fuller test to test the variables.[777] The logistic form of the instantaneous scrappage rate is stationary in levels. As such, there are no long-term trends within the scrappage rates that need to be captured and the scrappage model does not require lagged dependent variables to produce stationary residuals. However, to estimate unbiased estimators, the independent variables must also be stationary. The following table summarizes the order of integration of each of the considered regressions; the regression forms represent the form of the variable that is included in the considered models. All the variables considered are either I(0) or I(1), meaning that they should be run in either levels or first differences, respectively. This significantly simplifies the regressions.

[775] Hsiao, C. 1989. Analysis of Panel Data. *Cambridge University Press:* New York, NY. Available at: https://assets.cambridge.org/052181/8559/sample/0521818559ws.pdf. (Accessed: Feb. 13, 2024).
[776] Hsiao, C. 1989. Analysis of Panel Data. *Cambridge University Press:* New York, NY. Available at: https://assets.cambridge.org/052181/8559/sample/0521818559ws.pdf. (Accessed: Feb. 13, 2024).
[777] Lupi, C. 2019. Package 'CADFtest.' Available at: https://cran.r-project.org/web/packages/CADFtest/CADFtest.pdf. (Accessed: Feb. 13, 2024).

Table 4-5: Summary of Order of Integration of Considered Scrappage Variables

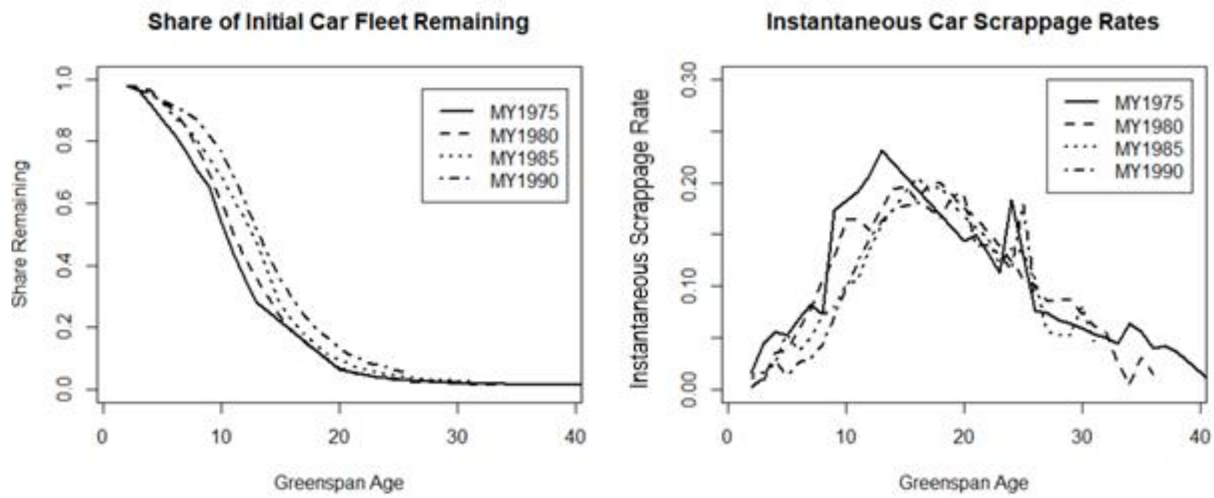
Scrappage Factor	Considered Measure	Source	Integration Order	Regression Form	Expected Sign
Scrappage Rate	Logistic of inter-annual scrappage rate for a MY/body style cohort	NVPP (I/Polk)	I(0)	Levels	N/A
Age	Age defined by the Greenspan and Cohen adjustment	NVPIIHS/Polk)	N/A	Levels	Polynomial[778]
Model year	Model year as defined from dataset	IP (IHS/Polk)	N/A	Levels	See MY Projections[779]
Business cycle indicator	Growth in GDP from previous year (annual, %)	BEA	I(0)	Levels	(+)
Prices of purchase	Average used vehicle prices by age in current year	No source; endogenous	N/A	N/A	(-)
Maintenance/ repair costs	Maintenance/repair CPI (fixed to 2016)	BLS	I(1)	Difference	(+)
Prices of substitutes	Average new vehicle prices less 30 months fuel savings in current year ($2018)	NADA, EIA, EPA trends	I(1)	Difference	(-)
Prices of usage	Cost-per-mile of MY/body style cohort in current year ($2018/100 mile)	EIA, EPA trends	I(1)	Difference	(+)
Prices of usage	Fuel share weighted fuel prices for MY/body style cohort in current year ($2018)	EIA, EPA trends	I(1)	Difference	(-)[780]

778 The effect of age on scrappage is an 'inverted-U' shape; the scrappage rate increases with age up to some age, after which the scrappage rate declines with age.
779 See the subchapter on modeling durability trends over time. Generally, scrappage rates will decrease with successive model years.
780 Since we include the cost-per-mile, we would expect that the change in fuel prices should capture only a capital constraint where increasing fuel prices will result in less capital to scrap a used vehicle and replace it.

4.2.2.3.2. Modeling Durability of Model Year Cohorts Over Time

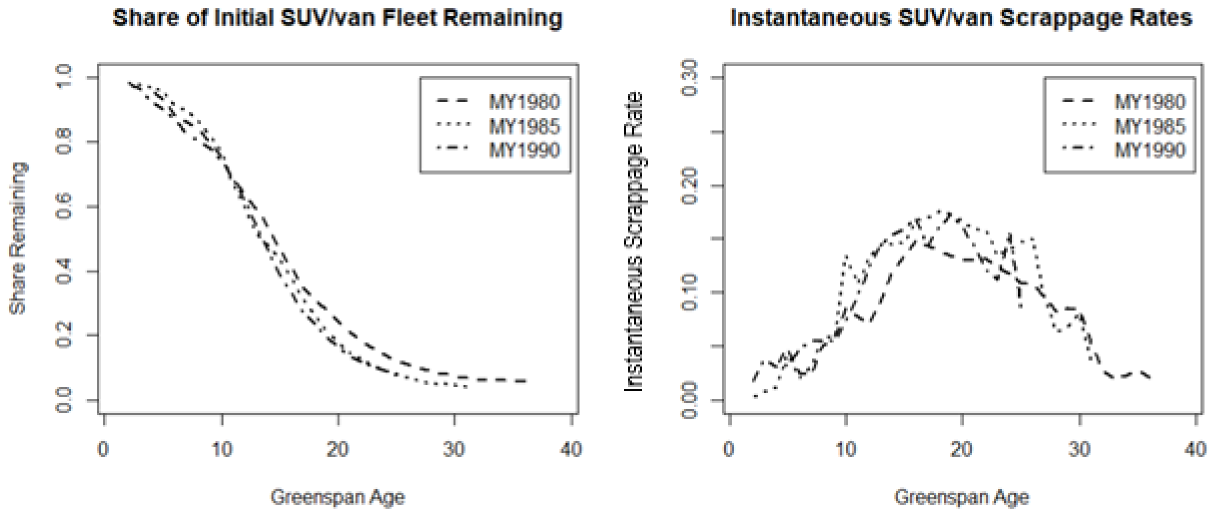
As explained in Chapter 4.2.2.2.1.1, engineering scrappage is largely determined by the age of a vehicle and the durability of a specific model year vintage. Because vehicle scrappage typically follows a roughly logistic function with age, the analysis uses a logistic function to capture the trend of vehicle scrappage with age but allows non-linear terms to capture any skew to the logistic relationship. The durability of successive model years generally increases over time. However, this trend is not constant with vehicle age—the instantaneous scrappage rate of vehicles is generally lower for later vintages up to a certain age but increases thereafter so that the final share of vehicles remaining converges to a similar share remaining for historically observed vintages. Figure 4-10 to Figure 4-12 shows the survival and scrappage patterns of different vintages with vehicle age for cars, SUVs/vans and pickups, respectively. Cars have the most pronounced durability pattern. Figure 4-10 shows that newer vintages scrap slower at first, but then scrap more heavily so that the final share remaining of cars is relatively constant by age 25 for all vintages.

Figure 4-10: Survival and Scrappage Patterns of Cars by Greenspan Age



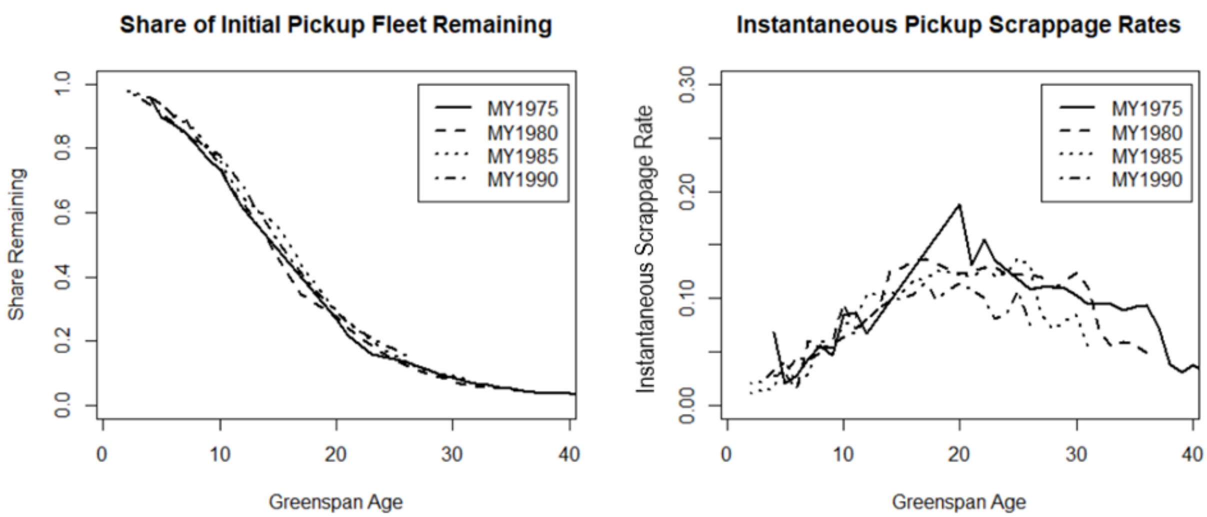
SUVs/vans have a less pronounced durability pattern. Model year 1980 actually lives longer than model years 1985 and 1990. This is likely due to a switch of SUVs/vans to be based on car chassis rather than pickup chasses over time. However, through the later model years, the durability trend is more like that of cars. The lack of a continuous trend in durability of SUVs/vans makes the way this trend is captured particularly important.

Figure 4-11: Survival of Scrappage Patterns of SUVs/Vans by Greenspan Age



There is no clear trend in durability for pickups. Like SUVs/vans, this makes parameterizing by using a form of vintage as a continuous variable problematic. Such a parametric form does not allow for each model year to have its own durability pattern. While HDPUVs are not modeled individually as a body type in this analysis, based on the composition of their fleet and their use, they are likely to most closely resemble pickups in terms of durability.

Figure 4-12: Survival and Scrappage Patterns of Pickups by Greenspan Age



NHTSA attempted to model the natural log of model year as a continuous variable interacted with age to capture an increasing but diminishing trend of vehicle durability for the younger ages. However, enforcing a parametric form on a continuous model year excluded the possibility of including model year specific fixed effects and required that durability to have a parametric trend with successive vintages. As seen above, SUVs/vans and pickups certainly do not follow such a trend, so that this constraint was too restrictive, at least for these body styles.

Instead of regressing the natural log of the vintage share in the remaining models, the agency tried several forms of the share remaining from the previous period as an independent variable, as seen in Table 4-6 through Table 4-8, below. Since the logistic instantaneous scrappage rate is stationary (it is independent of the previous periods' logistic instantaneous scrappage rate), the share remaining should not be endogenous. The specifications that include variables for the share remaining also include model year specific fixed effects, as well as the additional variables that were selected to capture the effect of economic cycles, changes in average new vehicle prices, and other non-engineering considerations on instantaneous scrappage rates.

4.2.2.3.3. Estimating the Scrappage Models

Below is the logistic scrappage equation used in the analysis supporting this final rule.

Equation 4-6: Scrappage Logistic Form

$$ln\left(\frac{S_{MY,CY}}{1-S_{MY,CY}}\right)=\beta_0{*}Age_{MY,CY}+\beta_1{*}Age^2{}_{MY,CY}+\beta_2{*}Age^3{}_{MY,CY}+\beta_3{*}Share\ Remaining_{MY,CY}+$$

$$\beta_4{*}(Age_{MY,CY}\ {*}\ Share\ Remaining_{MY,CY})+\beta_5{*}(Age^2{}_{MY,CY}\ {*}\ Share\ Remaining_{MY,CY})\ +$$

$$\beta_6{*}Diff(New\ Price\text{-}FS\text{-}TaxCredits)_{CY}+\beta_7{*}Diff(Fuel\ Price)_{CY}+\ \beta_8{*}Diff(CPM_{MY})_{CY}+$$

$$\beta_9{*}GDP\ Growth_{CY}+\beta_{10}{*}I[CY2009]\ +\ \beta_{11}{*}(I[CY2009]{*}\ I[Age\geq 25])+$$

$$\beta_{12}{*}I[CY2010]+\beta_{13}{*}(I[CY2010]{*}\ I[Age\geq 25])+FixedEeffects_{MY}$$

S represents the instantaneous scrappage rate in a period, so that the dependent variable is the logit form of the scrappage rates. Throughout the equation, *Diff* refers to the first difference of a given variable. As discussed in Chapter 4.2.2.3.1, above, it is important to ensure that the statistical properties of a variable do not change with time or else the variable will introduce statistical bias into the analysis. Because several of the variables considered in Table 4-5 were integrated of order 1, it is necessary to use the first difference (the calculated difference in its observed value from time *t* to time *t + 1*) in order to ensure stationarity.

Age represents the age of the model year cohort in a specific calendar year. The coefficient on the cubic age term is assumed to be zero for the van/SUV, pickup, and HDPUV specifications as this term is not necessary to capture the general scrappage trend for these body styles. *Share Remaining* represents the share of the original cohort remaining in that calendar year. These two components represent the engineering portion of scrappage—the inherent durability of a model year and the natural life cycle of how vehicles scrap out of a model year cohort as the cohort increases in age.

New Price—FS represents the average price of new vehicles minus 30 months of undiscounted fuel savings for all body styles. While tax credits related to the 2022 IRA are not present in the data during the years used to estimate the scrappage model, they are present in the years projected by the CAFE Model. To account for their effect on new vehicle prices in future years, and thus projected scrappage, the share of these credits that are passed through to consumers is also subtracted from the average new vehicle price used in the projected scrappage model. The central analysis assumes that the coefficient on the age interactions for this term are zero for all body styles, but NHTSA considered alternative specifications that allow the elasticity of scrappage to vary with age.

Fuel Price is the real fuel prices, weighted by fuel share (across all fuel types, but is overwhelmingly skewed toward gasoline in the historical data) of the model year cohort being scrapped. *CPM* represents the cost per 100 miles of travel for the specific body style of the model year cohort being scrapped under the current period fuel prices and using fuel shares for that model year cohort. These measures capture the response of scrappage rates to new vehicle prices, fuel savings, and to changes in fuel prices that make the used model year cohort more or less expensive to operate. Because these measures are all I(1), as discussed above in Table 4-5, the first difference of all of these variables is used in modelling.

GDP Growth represents the (real) GDP growth rate for the period. This captures the cyclical components of the macro-economy. Chapter 4.2.2.2.1.4, above, discusses how this specific measure was chosen, and what other measures were considered as alternative or additional independent variables.

I[CY2009] and *I[CY2010]* represent calendar year dummies for 2009 and 2010 when the CARS program was in effect; this controls for the impact of the program.

I[Age ≥ 25] represents an indicator for vehicles 25 years and older. The interaction of the calendar year dummies with this indicator allows for the effect of the CARS program to be different for vehicles under 25 versus vehicles 25 and older. Since only vehicles under 25 were eligible for the program, this flexibility is important to correctly control for the program.

FixedEffects represents a set of model year fixed effects used to control for heterogeneity across different model years. This is related to the durability and engineering scrappage.

Solving for instantaneous scrappage yields the following:

Equation 4-7: Instantaneous Scrappage

$$S=\frac{e^{\Sigma \beta_i X_i}}{1+e^{\Sigma \beta_i X_i}}$$

In the equation above, $\sum \beta_i X_i$ represents the right-hand side of the above model specification.

Table 4-6: Car Specifications with Alternative Durability Constructions

Variable	Share Remaining, Quadratic	Preferred: Share Remaining, Linear	Share Remaining, Constant
Age	0.0578317*** (0.0070468)	0.0951732*** (0.0058835)	0.4360045*** (0.0021804)
Age2	-0.0019635*** (0.0003689)	-0.0063290*** (0.0002880)	-0.0205609*** (0.0001130)
Age3	-0.0000414*** (0.0000061)	0.0000472*** (0.0000047)	0.0002313*** (0.0000025)
Share Remaining	-3.1435300*** (0.0414626)	-3.4186938*** (0.0343009)	-1.4338395*** (0.0256165)
Age *Share Remaining	0.3120942*** (0.0072003)	0.1806424*** (0.0026794)	
Age2 *Share Remaining	-0.0121010*** (0.0005793)		
Diff(New Price - Fuel Savings)	-0.0000951*** (0.0000013)	-0.0001009*** (0.0000014)	-0.0000912*** (0.0000020)
Diff(Real Gas Price)	-0.4458118*** (0.0200234)	-0.5176484*** (0.0166983)	-0.6428521*** (0.0220153)
Diff(Used Cost Per 100 miles)	0.0524257*** (0.0038726)	0.0620020*** (0.0034245)	0.0714549*** (0.0045965)
GDP Growth Rate	0.0456642*** (0.0008774)	0.0469495*** (0.0010729)	0.0563901*** (0.0010643)
CY2009	0.0732048*** (0.0190192)	0.2075985*** (0.0094498)	0.0839103*** (0.0121392)
CY2009, Ages 25+	0.4512855*** (0.0314314)	0.4920502*** (0.0218911)	0.4029622*** (0.0252641)
CY2010	0.2273621*** (0.0135031)	0.3150729*** (0.0089111)	0.4052745*** (0.0169191)
CY2010, Ages 25+	0.2995697*** (0.0238203)	0.2372077*** (0.0122188)	0.1398496*** (0.0233336)
Adj-R2	0.8989188	0.9001046	0.8957709

AIC	213	201	231
Woodridge AC P-Value[781]	0.0026154	0.0145811	0.0010401

*** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1

Table 4-7: SUVs/Vans Specifications with Alternative Durability Constructions

Variable	Share Remaining, Quadratic	Preferred: Share Remaining, Linear	Share Remaining, Constant
Age	0.2466527*** (0.0063507)	0.0460123*** (0.0055806)	0.4015673*** (0.0015458)
Age2	-0.0065623*** (0.0001252)	-0.0029204*** (0.0001212)	-0.0095063*** (0.0000358)
Share Remaining	0.0297029 (0.0901657)	-3.3452757*** (0.0554430)	0.7119660*** (0.0222985)
Age *Share Remaining	-0.0621384*** (0.0073936)	0.1825513*** (0.0030923)	
Age2 *Share Remaining	0.0112131*** (0.0003223)		
Diff(New Price - Fuel Savings)	-0.0000228*** (0.0000013)	-0.0000356*** (0.0000013)	-0.0000299*** (0.0000011)
Diff(Real Gas Price)	-0.2764171*** (0.0257452)	-0.4362834*** (0.0278925)	-0.2895806*** (0.0231274)
Diff(Used Cost per 100 Miles)	0.0524134*** (0.0043595)	0.0717750*** (0.0043034)	0.0531272*** (0.0034518)
GDP Growth Rate	0.0695386*** (0.0012301)	0.0657111*** (0.0009900)	0.0795823*** (0.0010000)
CY2009	0.4353784*** (0.0155607)	0.1828926*** (0.0129064)	0.6678445*** (0.0236451)
CY2009, Ages 25+	0.3581448*** (0.0206753)	0.6247703*** (0.0191476)	0.3282078*** (0.0248535)
CY2010	0.0924318*** (0.0167183)	0.2424634*** (0.0126816)	0.3936159*** (0.0158770)
CY2010, Ages 25+	0.3022435*** (0.0215352)	0.1385811*** (0.0298242)	-0.0734390** (0.0223489)
R2	0.9033051	0.9049046	0.8845334
AIC	173	160	288
Woodridge AC P-Value[782]	0.0035220	0.0486846	0.0000051

[781] Note: Wooldridge Test For AR(1) Errors In FE Panel Models implemented as 'pwartest' from the R Package 'plm'. The null hypothesis is that there is serial correlation in the errors, so that a p-value < 0.05 suggests that the errors are not serially correlated.
[782] Note: Wooldridge Test For AR(1) Errors In FE Panel Models implemented as 'pwartest' from the R Package 'plm'. The null hypothesis is that there is serial correlation in the errors, so that a p-value < 0.05 suggests that the errors are not serially correlated.

*** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1

Table 4-8: Pickup Specifications with Alternative Durability Constructions

Variable	Share Remaining, Quadratic	Preferred: Share Remaining, Linear	Share Remaining, Constant
Age	0.0776425*** (0.0064930)	0.0528728*** (0.0055778)	0.2629608*** (0.0015738)
Age2	-0.0023773*** (0.0001126)	-0.0018482*** (0.0000995)	-0.0057176*** (0.0000225)
Share Remaining	-1.5573629*** (0.1003296)	-1.9174078*** (0.0731793)	0.5012308*** (0.0306657)
Age *Share Remaining	0.1049521*** (0.0054214)	0.1310775*** (0.0034927)	
Age2 *Share Remaining	0.0012152*** (0.0002025)		
Diff(New Price - Fuel Savings)	-0.0000674*** (0.0000019)	-0.0000816*** (0.0000018)	-0.0000581*** (0.0000017)
Diff(Real Gas Price)	-0.2864880*** (0.0334947)	-0.5001835*** (0.0334884)	0.0798291** (0.0299877)
Diff(Used Cost per 100 Miles)	0.0441250*** (0.0056864)	0.0646677*** (0.0057105)	-0.0097471 (0.0052524)
GDP Growth Rate	0.0736057*** (0.0011368)	0.0582337*** (0.0012998)	0.0602333*** (0.0009533)
CY2009	0.5757490*** (0.0170277)	0.5752367*** (0.0170742)	0.5852774*** (0.0205956)
CY2009, Ages 25+	0.0705278* (0.0354674)	-0.0770359* (0.0343983)	0.1636518*** (0.0337895)
CY2010	0.1908829*** (0.0074929)	0.2808360*** (0.0070026)	0.2236518*** (0.0129120)
CY2010, Ages 25+	0.3659284*** (0.0136404)	0.4057619*** (0.0129972)	0.2123575*** (0.0153148)
R2	0.9228605	0.9193500	0.9170718
AIC	-45	-48	-32
Woodridge AC P-Value[783]	0.6073232	0.6683055	0.0516705

*** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1

As Table 4-6 shows, the linear form of the interaction of age and share remaining does not show evidence of autocorrelation and has the lowest Akaike Information Criterion (AIC – an estimator of prediction error and

[783] Note: Wooldridge Test For AR(1) Errors In FE Panel Models implemented as ‘pwartest’ from the R Package ‘plm’. The null hypothesis is that there is serial correlation in the errors, so that a p-value < 0.05 suggests that the errors are not serially correlated.

measure of model quality) and highest adjusted R-squared.[784] For these reasons, this is the preferred specification of the durability effect. Since the share remaining coefficient is negative and larger than the positive coefficient on the share remaining interacted with age, a cohort that has a higher share remaining at an early age will have a lower instantaneous scrappage rate in this period until a certain age and then a higher scrappage rate after that age. To find the age where the sign of the share remaining coefficient will switch from predicting a lower instantaneous scrappage rate to a higher one, one must take the ratio of the coefficient on the share remaining variable to the share remaining interacted with age—this suggests that at age 19, the sign of the share remaining variable flips. That is, the instantaneous scrappage rate of cars is predicted to be lower if the share remaining is higher until age 18, after which a higher share remaining predicts a higher instantaneous scrappage rate.

Table 4-7 shows, the linear interaction of age and share remaining is the only specification of the durability effect for SUVs/vans that do not show autocorrelation in the error structure. The linear interaction of age and share remaining has the lowest AIC and highest R-squared; for this reason, this is the preferred specification of the durability effect for SUVs/vans. The signs for share remaining and share remaining interacted with age show a similar trend as that to cars. Taking the ratio again of the share remaining to the share remaining interacted with age, for ages 0 to 18 a higher share remaining predicts lower instantaneous scrappage, and for ages beyond 18 it predicts a higher instantaneous scrappage rate.

Table 4-8 shows, all specifications of the durability effect for pickups do not show autocorrelation in the error structures. However, similar to cars and SUVs/vans, the linear interaction of age and share remaining has the lowest AIC and highest adjusted R-squared. For this reason, this is the preferred specification for all body styles. Taking the ratio of the coefficient on share remaining to share remaining interacted with age shows that a higher share remaining will predict a lower instantaneous scrappage rate in the next period for ages 0 through 14, but a higher instantaneous scrappage rate for ages 15 and older.

4.2.2.3.3.1. Projecting Durability in the CAFE Model

The left graphs in Figure 4-13 through Figure 4-15 show the fixed effects for the preferred scrappage specifications for cars, vans/SUVs, and pickups, respectively. For all body styles there is a general downward trend in the fixed effects. This suggests an increase in the durability over successive model years. However, since the panel datasets are unbalanced, there is likely potential bias for the fixed effects that include only certain ages. This makes projecting the durability increase from the fixed effects a little more complicated than merely fitting to all fixed effects. First, NHTSA determined which part of this trend is likely due to increases in vehicle durability (and should be projected forward) and which part of the trend may conflate other factors.

The right graphs in Figure 4-13 through Figure 4-15 show the average observed logistic scrappage rates by model year for all ages where data exist. As can be seen, the average observed scrappage rates decline dramatically for model years after 1996 for all body styles. There are two reasons this trend exists. First, as the figures show, the instantaneous scrappage rate generally follows an inverted u-shape with respect to vehicle age. The instantaneous scrappage rates generally peak between ages 15 and 20 for all body styles. Model year 1996 is the first model year which will be at least age 20 at the most recent year of data used to estimate the scrappage models (calendar year 2016). This means that all model years newer than 1996 have likely not yet reached the age where the instantaneous scrappage rate will be the highest for the cohort. Accordingly, the fixed effects could be biased downwards (consistent with the sharper downward slope in the fixed effects for most body styles for model years beyond 1996) because of the unbalanced nature of the panel, and not because of an actual increase in inherent vehicle durability for those model years.

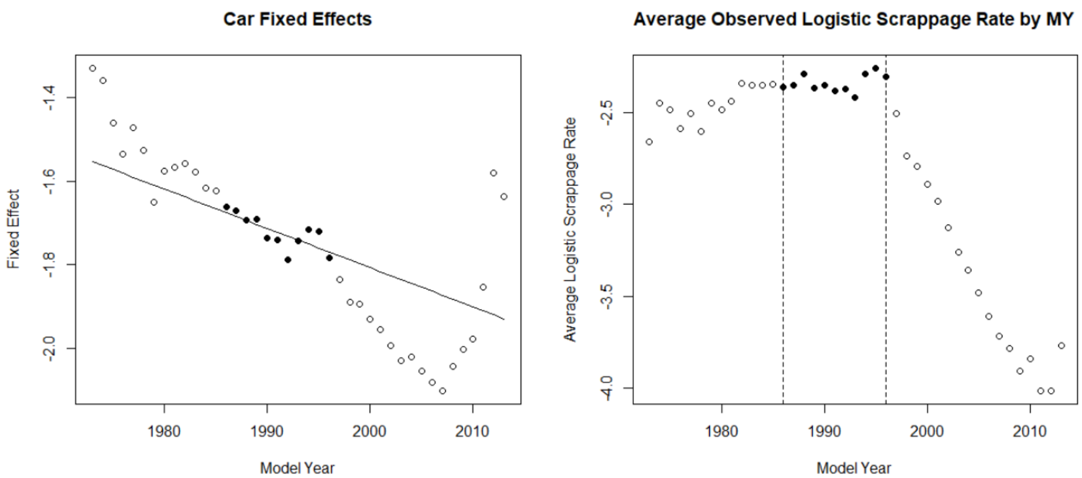
The second reason the average logistic scrappage rates for model years before 1996 is more stable is because each data point in the average has increasingly less effect on the average as more data exist. For model years 1996 and older there are at least 18 data points (we start the scrappage at age 2, by which point

[784] Note that the parameters of these scrappage models are estimated on data where the stock of used vehciles is comprised predominantlu of ICE vehicles. It is not clear whether scrappage decisions will substantantively change in future years when ZEVs, SHEVs, and PHEVs constitute a larger share of new vehicle shipments, as consumer demand characacteristics might differ between these vehicle options in the used car decision-making process. The available data and methods used in this rulemaking constitute to NHTSA's knowledge the best available approach to measure the scrappage decision. NHTSA continues to monitor the literature for the best data and methods to estimate its scrappage model.

effectively all of a model year has been sold), and each will have a smaller effect on the average than for newer model years with fewer observations. For these reasons, the average observed logistic scrappage rate is more constant for model years before 1996. As a result, we do not consider the trend in fixed effects after model year 1996 to rely on enough historical data to represent a trend in vehicle durability, as opposed to a trend in the scrappage rate with vehicle age.

In considering which model year fixed effects should be considered in projecting durability trends forward, another important factor is whether there are discrete shifts in the types of vehicles that are in the market or category of each body style over time. For cars, an increasing market share of Japanese automobiles, which tend to be more durable over time might result in fixed effects for earlier model years being higher. This trend is shown in the fixed effects in Figure 4-13, which follow a steeper trend before model year 1980.

Figure 4-13: Trends in Fixed Effects for Preferred Car Specification



For vans/SUVs, earlier model years are more likely to be built on truck chassis (body-on-frame construction) instead of car chassis (unibody construction). Since pickups tend to be more durable, the earlier fixed effects are likely to be lower for vans/SUVs for earlier model years. The 1984 Jeep Cherokee was the first unibody construction SUV.[785] As Figure 4-14 shows, the fixed effects before 1986 show inconsistent trends; these are likely due to changes in what was considered a van/SUV over time. For this reason, NHTSA builds the trend of fixed effects from model years 1986 to 1996.

785 Hunting, B. 2021. 10 Interesting Facts from the History of the Jeep Cherokee. Last revised: Nov. 26, 2021. Available at: https://www.autoguide.com/auto-news/2018/01/10-interesting-facts-from-the-history-of-the-jeep-cherokee.html. (Accessed: Feb. 13, 2024).

Figure 4-14: Trends in Fixed Effects for Preferred Van/SUV Specification

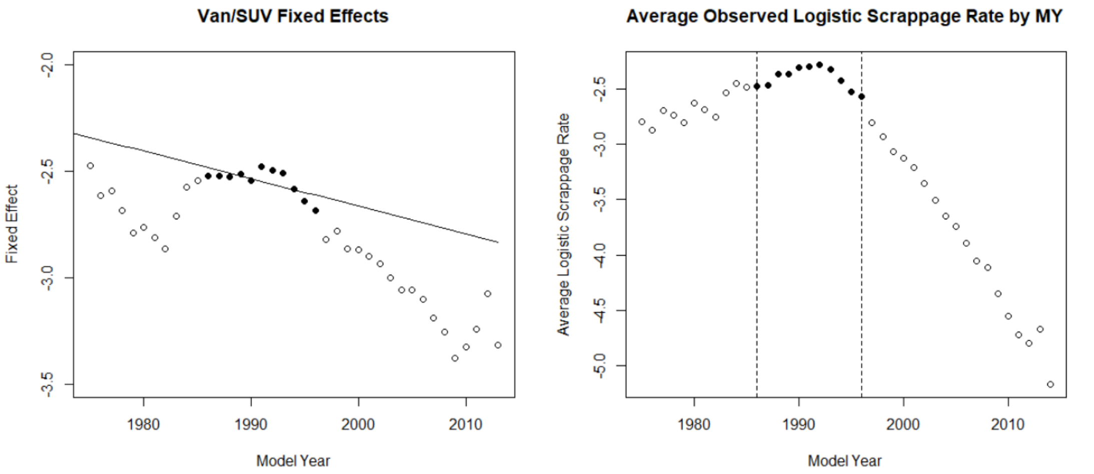
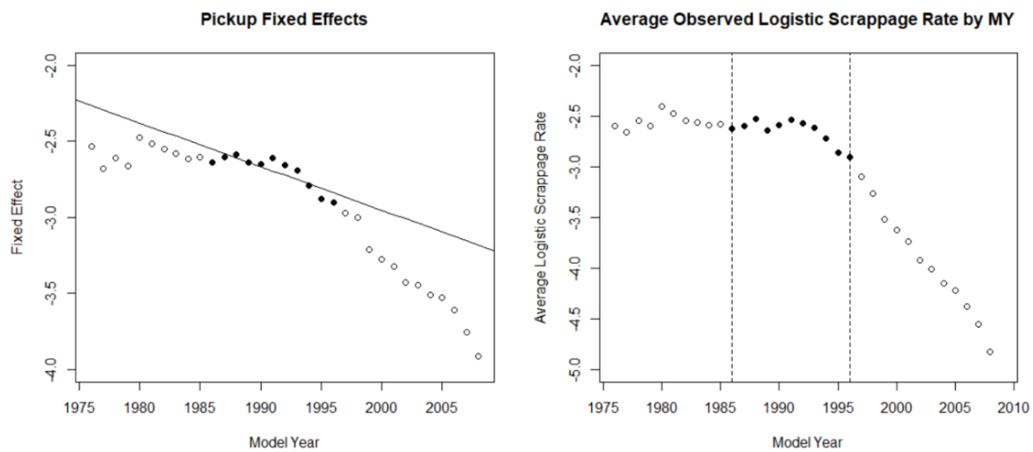


Figure 4-15: Trends in Fixed Effects for Preferred Pickup Specification



While the trend for pickups and cars could be extrapolated before 1986, NHTSA opted to keep the fixed effects included constant for all body styles. Thus, the projections are built from model year 1986 to model year 1996 fixed effects. Table 4-9 below shows the linear regressions shown as the line on the left side of Figure 4-13 through Figure 4-15. The durability cap represents the last model year where the durability trend is assumed to persist. The agency caps the durability impacts at model year 2005, as data beyond this point do not exist for enough ages to determine if durability has continued to increase since this point. This cap implies that model years after 2005 are assumed to have the same initial durability as model year 2005 vehicles. Since there is a limit to the potential durability of vehicles, this acts as a bound on this portion of the scrappage model (which, in turn impacts simulated fleet size and average age).

Table 4-9: Durability Inputs in the CAFE Model

Coefficients	Inputs	Cars	Vans/SUVs	Pickups
β_{12}	Intercept	21.13195	25.488	54.52891
β_{13}	MY	-0.01141	-0.01364	-0.02879
β_{14}	MY Durability Cap	2005	2005	2005

The durability projections enter the scrappage equation in the CAFE Model simulations in accordance with the following equation:

Equation 4-8: Durability Projections and Scrappage Equation[786]

$$ln\left(\frac{S_{MY,CY}}{1-S_{MY,CY}}\right)=\beta_0*Age_{MY,CY}+\beta_1*Age^2{}_{MY,CY}+\beta_2*Age^3{}_{MY,CY}+$$

$$Share\ Remaining_{MY,CY}*(\beta_3+\beta_4*Age_{MY,CY})+$$

$$Diff(New\ Price\text{-}FS\text{-}TaxCredits)_{CY}*(\beta_5+\beta_6*Age_{MY.CY}+\beta_7*Age^2{}_{MY.CY}+\beta_8*Age^3{}_{MY,CY})+$$

$$\beta_9*Diff(Fuel\ Price)_{CY}+\beta_{10}*Diff(CP100M_{MY})_{CY}+$$

$$\beta_{11}*GDP\ Growth_{CY}+\beta_{12}+\beta_{13}*MY_{MY}-ifelse(MY_{MY}>\beta_{14},\beta_{13}*(MY_{MY}-\beta_{14}),0)$$

The intercept enters as a constant added to the predicted logistic of the instantaneous scrappage rate. The model year slope enters as the model year for all model years older than 2005 and enters as 2005 for all model years 2005 and newer.

Once the predicted logistic scrappage rate is calculated in the CAFE Model (including the projections of the fixed effect portion of the equation), the future population of model year cohorts can be predicted. The instantaneous scrappage can be calculated directly from *S*. It identifies the share of remaining vehicles in each calendar year that are scrapped in the next year. The population of vehicles in the next calendar year can be calculated as follows:

Equation 4-9: Calculation of Population of Vehicles in the Next Calendar Year

$$Population_{MY,\ CY+1}=Population_{MY,CY}*(1-s_{MY,CY})$$

This process iterates at the end of the CAFE Model simulation to determine the projected population of each model year in each future calendar year. This allows the calculation of VMT, fuel usage, pollutant and CO_2 emissions, and associated costs and benefits. The CAFE Model Documentation released with this final rule further details how the scrappage model is projected within the simulations.

4.2.2.3.3.2. Decay Function for Oldest Ages

Nearly six percent of the model year 2015 van/SUV fleet and eight percent of the pickup fleet is projected to persist until age 40. This is unrealistic, and likely due to the fact that the agency does not observe enough model years for those ages thus and over-predicts the impact of durability increases for those ages. For this reason, the agency uses a scrappage curve with an accelerated decay function to predict instantaneous scrappage beyond age 30 for all classes. Table 4-10 below, shows the inputs used for this analysis.

Table 4-10: Decay Function Inputs

Coefficients	Inputs	Cars	Vans/SUVs	Pickups
β_{15}	Decay Age	30	30	30
β_{16}	Final Survival Rate	0.01	0.025	0.025

The agency selected to have the decay function begin operating at age 30 as the observed historical trends run through age 30.

[786] While tax credits related to the 2022 Inflation Reduction Act are not present in the historical data used to estimate the scrappage model, they are included in the CAFE Model and thus impact the price paid for new vehicles by consumers. Fifty percent of these credits are assumed to pass through to consumers in the form of lower prices. This share is perturbed in the sensitivity analysis.

The decay function is implemented in the model using the following conditions for the coefficients in Table 4-10:

$$If\ (age<\beta_{15}),\ S=\frac{e^{\Sigma\beta_i X_i)}}{1+e^{\Sigma\beta_i X_i)}}$$

$$And:\ Population_{MY,\ CY+1}=Population_{MY,CY}*(1-S_{MY,CY}).$$

$$If\ (age>=\beta_{15}),$$

$$Population_{MY,\ CY+1}=Population_{MY,CY=\beta_{15}}*exp^{rate*t}$$

$$Where:t=\left(age+1-\beta_{15}\right)$$

$$And:\ rate=\frac{ln\left(\frac{(\beta_{16})}{Population_{MY,CY=\beta_{15}}}\right)}{40-\beta_{15}}$$

Here, the population for ages beyond the start age of the decay function depends on the population of the cohort at that start age and the final share expected for that body style at age 40. Then the model calculates and applies the rate of decay necessary to make the final population count equal that observed in the historical data.

4.2.2.3.4. Other Variables Considered

In addition to the variables included in the scrappage model, the agency considered several other variables that likely—either directly or indirectly—influence scrappage in the real world. As explained in more detail in the forthcoming paragraphs, these variables were excluded from the model either because of a lack of underlying data or due to modeling constraints. Their exclusion from the model is not intended to diminish their importance, but rather highlights the practical constraints of modeling complex decisions like vehicle scrappage in both an econometric and (subsequently) simulation context.

As noted earlier, households will retire used vehicles when their market value drops below the cost of maintenance necessary to keep them in service, so how maintenance costs change as vehicles age and accumulate use plays a critical role in determining when they are retired. However, suitable measures of maintenance costs are difficult to locate, because they need to reflect both increases in maintenance costs with vehicle age and historical variation in the general level of maintenance costs for all vehicles. The most comprehensive measure is the BLS' maintenance and repair component of the CPI, but it reflects only variation in average maintenance costs over time and does not reflect how the level or frequency of maintenance increases for older vehicles. This limits its usefulness in a panel model, since it can only be included as a calendar year effect, and using the measure in that role resulted in a poorer fit, so the agency excluded it from the model. If age- specific repair cost measures become available in the future, the agency will consider including them in future model specifications.

The market value of a vehicle at the time of scrappage is equal to a combination of the price of the parts that can be salvaged and the value of the recoverable scrapped metal. The agency considered including the value of steel and iron to capture the scrappage value of vehicles. However, the material composition and mass of vehicles has changed over time meaning that the absolute amount of recoverable scrap steel is not constant. To appropriately estimate the value to scrap a vehicle, the agency would need to know the average weight of recoverable steel by vintage *and* the quantity and value of other recoverable materials. The agency is unaware of any data granular enough to provide estimates of these values.

Further, projecting the future value of the recoverable scrap metal would involve computing the amount of recoverable steel under all scenarios of fuel economy standards, where mass and material composition are assumed to vary across all alternatives. The agency attempted to use a coarse approximation of scrappage value by using the BLS scrap steel CPI; similar to maintenance, including the variable diminished the fit of the model. It is also a consideration that, over time, vehicles leave U.S. registration rolls for reasons other than true scrappage (typically export to less wealthy nations where the vehicle still represents a positive value proposition to potential buyers), which would not be as strongly affected by the price of scrap steel.

The scrappage model controls for vehicle characteristics across model years through fixed effects. As an alternative, the agency considered a more granular approach of estimating the impact of discrete vehicle traits, such as horsepower to weight, zero to sixty acceleration time, and average curb weight. However, including these individual traits produced a poorer fit than the model with fixed effects, and showed evidence of autocorrelation in the errors. Similarly, the agency considered using terms that would more directly capture the value of improved fuel economy in newer vehicles, such as the CPM of new vintages, than subtracting the first 30 months of undiscounted fuel prices from the price of new vehicles.[787] These variables did not improve the fit of the model and would be inconsistent with how the agency approaches consumer valuation of fuel economy throughout the rest of the analysis.

The quantity of new vehicles purchased and scrappage rates seem intuitively interconnected; when new vehicle sales increase, demand for older vehicles decreases, leading to higher scrappage rates. When the agency tested new vehicle sales in the model, the model's fit decreased and the direction of the coefficient was counterintuitive. It also introduced evidence of autocorrelation in the error structure for cars and reduced the effect of the change in fuel prices by two orders of magnitude for vans/SUVs. It seems quite unlikely that fuel price sensitivities would differ so vastly between model types. For these reasons, the scrappage model excludes the change in new vehicles sales. The agency also considered including changes in vehicle stock, but this similarly did not improve the fit of the scrappage models—and doing so limited the ability to link the sales and scrappage models in future versions of the model.

Higher interest rates increase the cost to purchase new vehicles, which should increase the incentive for households to hold onto existing vehicles. For some households, higher interest rates could act as a barrier to entry, although, the households excluded from the new vehicle market because of a modest change in interest rates are much more likely to be in the market for a used vehicle and their purchasing decisions are unlikely to be heavily influenced by interest rates. The agency tested interest rates in the model using the average real interest rate on social security trust public-debt obligations. While this is not a perfect measure of auto loan interest rates, the two are closely correlated, so that that most of the effect of auto loan rates should be captured by using the interest rate facing the federal government. For vans/SUVs the model with interest rates had a poorer fit and showed evidence of autocorrelation in the error structures. For pickups, including interest rates changed the sign on CPM. Interest rates do not affect CPM as CPM measures only the post-sale operating cost.

4.3. Estimating Total Vehicle Miles Traveled

4.3.1. Overview of the Process

Forecasts of total vehicle use – as measured by the number of vehicle miles traveled (VMT) – are a core input to NHTSA's analysis of the effects of establishing alternative standards for future model years. The agency's CAFE Model calculates several slightly different components of VMT for each calendar year included in the analysis period (here, 2022 through 2050), which are used for different purposes in the analysis. Briefly, these include:

- Unadjusted "non-rebound" or "pre-rebound" VMT is calculated by multiplying average annual VMT for vehicles of each age (ranging from new to 40 years) and body-style during a future calendar year by the number remaining in use during that year and summing the results. This measure incorporates the effect on vehicle use of differences in fuel prices between future calendar years and the 2016 base year when the mileage accumulation schedules were developed but excludes the effects on vehicle use of fuel economy and efficiency improvements after the 2016 base year. This latter feature explains why it is referred to as non-rebound VMT. The purposes of excluding the effect of improved fuel economy and

[746] While tax credits related to the 2022 Inflation Reduction Act are not present in the historical data used to estimate the scrappage model, they are included in the CAFE Model and thus impact the price paid for new vehicles by consumers. Fifty percent of these credits are assumed to pass through to consumers in the form of lower prices. This share is perturbed in the sensitivity analysis.

efficiency from this measure is to ensure that all differences in VMT and its consequences among the regulatory alternatives evaluated here reflect variation in the levels of fuel economy or efficiency they require. We calculate non-rebound VMT for both the light-duty and HDPUV fleets.

- "Forecast" car and light truck VMT is calculated for each future calendar year using the Federal Highway Administration's (FHWA) light-duty VMT forecasting model in conjunction with the same macroeconomic forecasts used elsewhere in the CAFE Model. This forecast is used to adjust non-rebound VMT to be identical among the reference baseline and all regulatory alternatives during each calendar year, by scaling average annual VMT for vehicles of each age up or down as necessary to make total adjusted non-rebound VMT match each year's forecast VMT. This constraining process is applied only for car and light truck VMT and is not used for HDPUVs.
- "Reallocated VMT" is the difference in total VMT between that forecast using the FHWA model and unadjusted non-rebound VMT during any future calendar year. It is the amount by which total unadjusted non-rebound VMT must be increased or reduced during each future calendar year so that adjusted non-rebound VMT equals the FHWA forecast of VMT for that year. Again, reallocated VMT is only calculated and used for cars and light trucks.

The procedure used to calculate each of these VMT measures and the purpose for which it is used in the analysis are described in detail in the following subchapters.

In the CAFE Model, total annual VMT is estimated as the product of average annual use of each vehicle cohort (usually defined by vehicle type, model year when originally produced, and current age) making up the fleet and the number of vehicles from that model year cohort remaining in use, which is itself a function of historical new vehicle sales and vehicles' retirement (or "scrappage") rates over their lifetimes.[788] In conjunction with the composition of the "inherited" vehicle fleet by type (e.g., cars, SUVs/vans, pickups) and age at the outset of the analysis period, these three components—average annual use of vehicles of different ages and body styles, sales of new vehicles, and scrappage of older vehicles—jointly determine projected total VMT for future years under each regulatory alternative considered.

The CAFE Model's simulations using this approach provide estimates of aggregate light-duty VMT that are closely comparable to other well-regarded VMT estimates. However, because decisions about alternative stringencies for CAFE standards examine their incremental costs and benefits across alternatives, it is more important that the analysis capture variation in VMT among the reference baseline and regulatory alternatives than to accurately predict total VMT for a specific scenario. To accomplish this, the CAFE Model incorporates a model of aggregate VMT developed by the U.S. Department of Transportation's Volpe Center to produce the FHWA official annual VMT forecasts. The CAFE Model's internally constructed forecasts of total VMT under different regulatory alternatives in each future year are initially constrained to be identical to those produced by the FHWA model.[789]

The CAFE Model first uses the FHWA model to develop a forecast of total light-duty VMT for each future calendar year spanned by the analysis (currently 2022 through 2050) that reflects forecasts of the U.S. population, future economic conditions, fuel prices and fleet average fuel economy, and consumer confidence levels. As described in more detail below, this forecast of total VMT is interpreted as "pre-rebound" or "non-rebound" travel, and total VMT under the reference baseline and each regulatory alternative being considered is constrained to match this forecast during each calendar year of the analysis period. This produces the desired effect of making any differences in VMT among regulatory alternatives during future calendar years a consequence of differences in the amount of rebound-effect driving associated with the improvement in fuel economy each regulatory alternative requires.

NHTSA's CAFE Model uses a combination of each year's "top-down" forecast of total light-duty VMT generated by the FHWA model and its internally generated or "bottom-up" forecast to represent the

[788] While there is heterogenity in terms of average VMT within a vehicle type/model year cohort, NHTSA does not account for this in its non-rebound VMT allocation. This may over or understate some off the effects estimated by the CAFE Model if vehicle usage is highly correlated with other attributes that also determine the size of the effects.

[747] There is a minor and consistent discrepancy between the forecasts of light-duty VMT issued by FHWA and those generated using the CAFE Model, because the former include class 2b and 3 light-duty vehicles while the CAFE Model and analysis exclude these vehicles. Unfortunately, it is not easily possible to disaggregate FHWA's historical estimates or forecasts of light-duty VMT between light-duty vehicles (classes 1 and 2a) and MDPUVs (classes 2b and 3).

composition of total VMT. This latter approach combines the composition of the fleet among car and light truck cohorts of different vintages and ages with the average utilization of each cohort to determine a base distribution and level of VMT in each calendar year. Each year's forecast of aggregate VMT produced using the "bottom up" approach is then adjusted to match the "top down" forecast of total VMT for that same calendar year, while preserving the proportional distribution of total vehicle use among the car and light truck model year cohorts comprising that year's fleet.

NHTSA believes that a household-level model of vehicle ownership and use—if one could adequately and reliably capture the myriad circumstances under which families and individuals make decisions relating to vehicle purchase, use, and disposal—could more accurately predict the outcomes of those decisions, since they are made at the household level. However, NHTSA also believes that it is not necessary or appropriate to model a national program at that level of disaggregation in order to produce results that can usefully inform policy decisions, since the most useful information for policymakers relates to national-scale impacts of potential policy choices. No other element of the rulemaking analysis is represented or analyzed at the household level, and the errors introduced by allocating specific vehicles to individual households over the course of three decades would probably outweigh any inaccuracies associated with the estimation of these effects in aggregate.

NHTSA has attempted to incorporate estimates of changes to the new and used vehicle markets at the most practical levels of aggregation and has worked to ensure that these effects produce fleetwide VMT estimates that are consistent with current projections reflecting our economic assumptions. While future work will always continue to explore approaches to improve the realism of CAFE policy simulation, there are important differences in the objectives and design of small-scale econometric research and the kind of flexibility that is required to assess the impacts of a broad range of regulatory alternatives over multiple decades, as is the case here.

4.3.2. Developing the Mileage Accumulation Schedules

To account properly for the values of consumer and societal costs and benefits associated with vehicle usage under various CAFE alternatives, it is necessary to estimate the portion of these costs and benefits occurring during each calendar year that are attributable to the ownership and use of vehicles from each model year cohort. Doing so requires some estimate of how many miles the average vehicle of each body type is expected to be driven during each year (i.e., at each age) throughout its life. We refer to these as "mileage accumulation schedules." As described in greater detail below, these mileage accumulation schedules represent an initial estimate of average annual vehicle use at each age during some base year and are subsequently adjusted in each future calendar year based on forecasted fuel prices and the aggregate travel demand determined by a separate forecasting model. For this analysis, NHTSA is relying on a set of mileage accumulation schedules that were constructed from a statistical analysis of millions of unique vehicles followed over their lives, during which odometer readings were recorded at uneven intervals.

4.3.2.1. Data Used to Develop the Schedules

Unlike cross-sectional data, which provide a "snapshot" of the usage of vehicles of different ages at a single point in time, panel data track the use of vehicles over time as they reach different ages and accumulate mileage. Including this temporal dimension resolves many of the limitations imposed by cross-sectional data, which restricted some of the agency's earlier rulemakings. The data source used to construct the current mileage accumulation schedules contains sequential odometer readings for a very large sample of individual vehicles tracked at the vehicle identification number (VIN) level over time. The data vendor, IHS Markit – Polk, accumulates odometer readings for individual vehicles from state inspection programs, title changes, and maintenance events, among other sources. The IHS-Polk dataset includes observations of a specific vehicle's odometer readings over the course of many years, capturing its accumulated lifetime mileage at multiple ages.

By using the observation date and accumulated miles (represented by the odometer reading), NHTSA computed the rate of driving (miles per year, or month) between observations for each vehicle. This method provides more reliable estimates of variation in vehicle use with increasing age than computing a simple ratio of total miles traveled to age. This is an improvement over schedules built from cross-sectional data, which implicitly assume the VMT-to-age ratio across vehicle ages.[790] In particular, calculating the rates of mileage accumulation using successive observations of the same vehicle explicitly resolves the attrition bias (where some vehicles disappear from a cross-sectional data sample because of the intensity with which they were used) and matches the approach to estimating driving rates with panel data in other studies.[791]

4.3.2.2. Methodology for Constructing the Schedules

The data used to construct the schedules initially included between two and fifty odometer readings from each of over 251 million unique vehicles within the dataset. While most of the readings had plausible reading dates, odometer counts, and implied usage rates, some of the readings appeared unrealistic and received additional scrutiny. We developed and applied criteria to identify and remove readings that were likely to reflect recording errors. For example, odometer readings predating the commercial release of the vehicle, showing negative VMT accumulation over time, or taken too closely together to provide meaningful insight into annual vehicle usage, were removed from the analysis. Such "cleaning" of datasets is typically necessary, and each step in the process was recorded and documented clearly. Table 4-11 shows the number of VINs, reading pairs, and average readings per VIN by body style for the remaining readings.[792]

Table 4-11: Summary of IHS Polk VMT VIN and Reading Data by Body Style

Body Style	Number of VINs Included	Number of Reading Pairs	Mean Readings per VIN
Car	92,016,334	287,512,165	4.1
SUVs/vans	66,857,117	212,656,710	4.2
Pickups	29,926,984	83,208,986	3.8
MDPUV	10,565,986	29,409,766	3.8

We created a random sample of one million reading pairs from the refined dataset where each pair represented an initial odometer/date reading and a subsequent odometer/date reading from the same vehicle. Analysis of the entire dataset was judged to be overly demanding computationally and unnecessary to provide the desired level of statistical precision in estimates of average vehicle use. Two conditions were created for sampling. The first controlled for IHS-Polk's censoring in the odometer readings recorded in the dataset (described below), while the second ensured the usage data were not biased by survival and represented usage rates over a relatively short period of time. Further analysis suggests that shorter periods between readings are correlated with higher usage rates, so further filtering of the data sample was considered in the regression analysis. Once these filters were applied, we considered several polynomial fits to the average odometer readings by age and body style and used our preferred models to construct the mileage accumulation schedules used in this analysis. Additional details of this process are described below.

The reported odometer readings are limited to a maximum value of 250,000 miles. For this reason, we excluded readings recorded exactly as 250,000 miles. The censoring could bias estimates of usage rates if odometer readings and future usage rates are correlated, as seems likely to be the case. Vehicles with reported odometer readings of exactly 250,000 miles in the dataset almost certainly have higher true odometer readings. While we intend to reconcile this limitation of the dataset in future work, the benefits of observing actual usage through 30 years of a vehicle's life more than compensate for the limitation.

The IHS-Polk dataset is conditional on survival, so it represents the usage of vehicles remaining in use at the time of the sample (the end of the first quarter of 2017). In this way, it captures the actual observed usage rates of vehicles surviving to their current ages on that date. This raises an important concern: if usage rates from earlier ages and survival are correlated, which they are likely to be, then including the readings for a 30-

[790] Lu, S. 2006. Vehicle Survivability and Travel Mileage Schedules. DOT HS 809 952. Available at: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/809952. (Accessed: Feb. 13, 2024).
[791] The use of the IHS Polk panel data provides other advantages to the calculation of mileage accumulation schedules in this context, including more accurate determination of vehicle age and coverage not avaiable from other data sources. These advantages are discussed in detail in prior rulemakings. For reference, *see* 84 FR 24678 (Apr. 30, 2020).
[792] Data in this table for cars, SUVs, and pickups are identical to values used in the 2022 FR. For the final rule, agency staff classified HDPUV vehicles in the IHS Polk dataset. HDPUV identification was based on a combination of reported GVW and vehicle make-model-trim name.

year-old vehicle when it was 10 years old will bias the estimated usage rates of 10-year-old vehicles downward because vehicles that survive to advanced ages tend to have been used less heavily than vehicles of the same vintage that were retired at earlier ages. To mitigate this issue, we applied a second filter when sampling the data set: we only included readings where the date of the second reading in the pair is January 2015 or later. This reduces any potential bias introduced by the joint probability distribution of usage and survival to only those vehicles scrapped between January 2015 and the first quarter of 2017. This decision balances the drawbacks of losing information on vehicles of older ages that are not well-represented in the sample by excluding too many of these vehicles against the potential for biasing the estimates of usage by age.

The distribution of vehicle use at a given age can initially be wide, but tends to narrow over time, as usage across vehicles tends to converge towards lower levels. Figure 4-16 illustrates the distribution of observed VMT, by age, for SUVs (figures constructed for cars and pickup trucks showed similar patterns) across a 10 million-record random sample of the IHS-Polk odometer data. As the figure shows, the distribution of observed annual usage is wide at early ages and then both the mean annual VMT and the range of observations decreases gradually with increasing age.

Figure 4-16: Distribution of SUV Usage Rates by Age

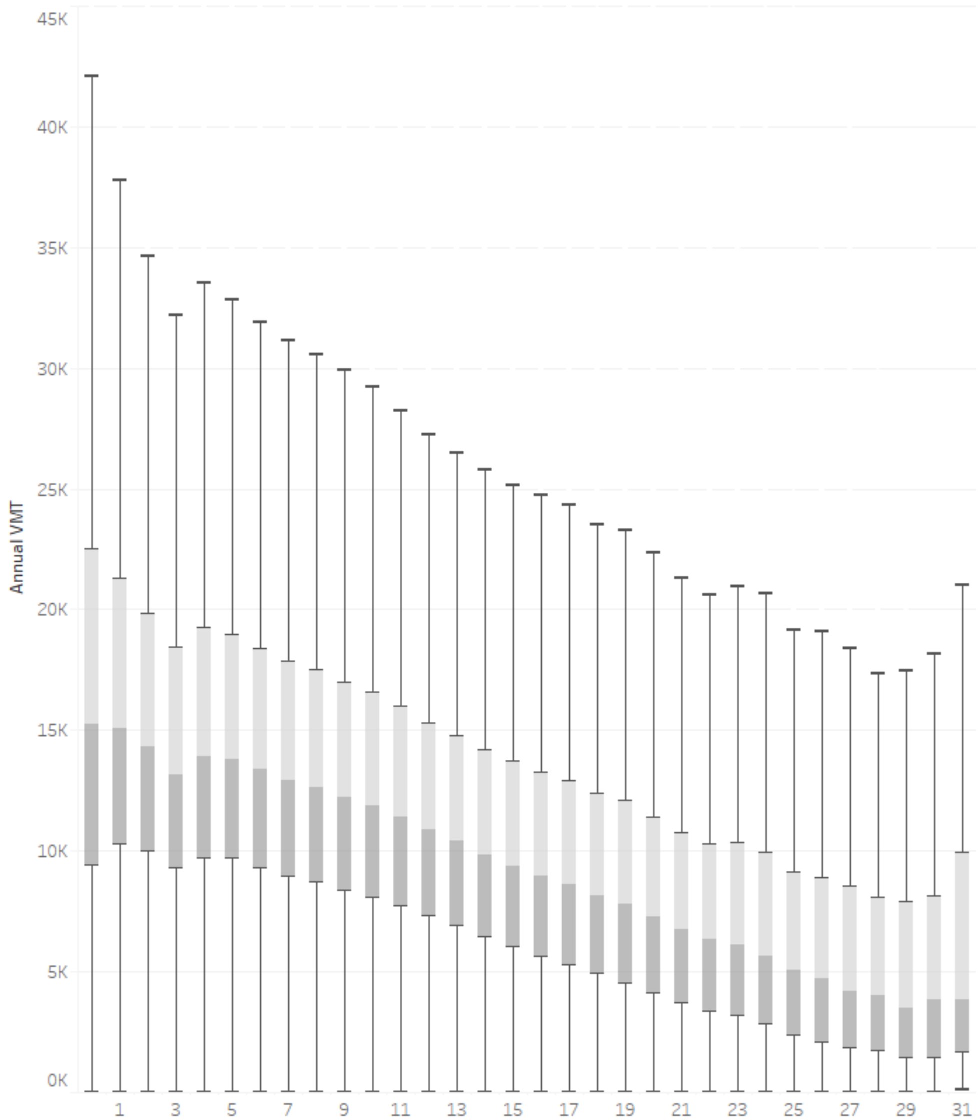
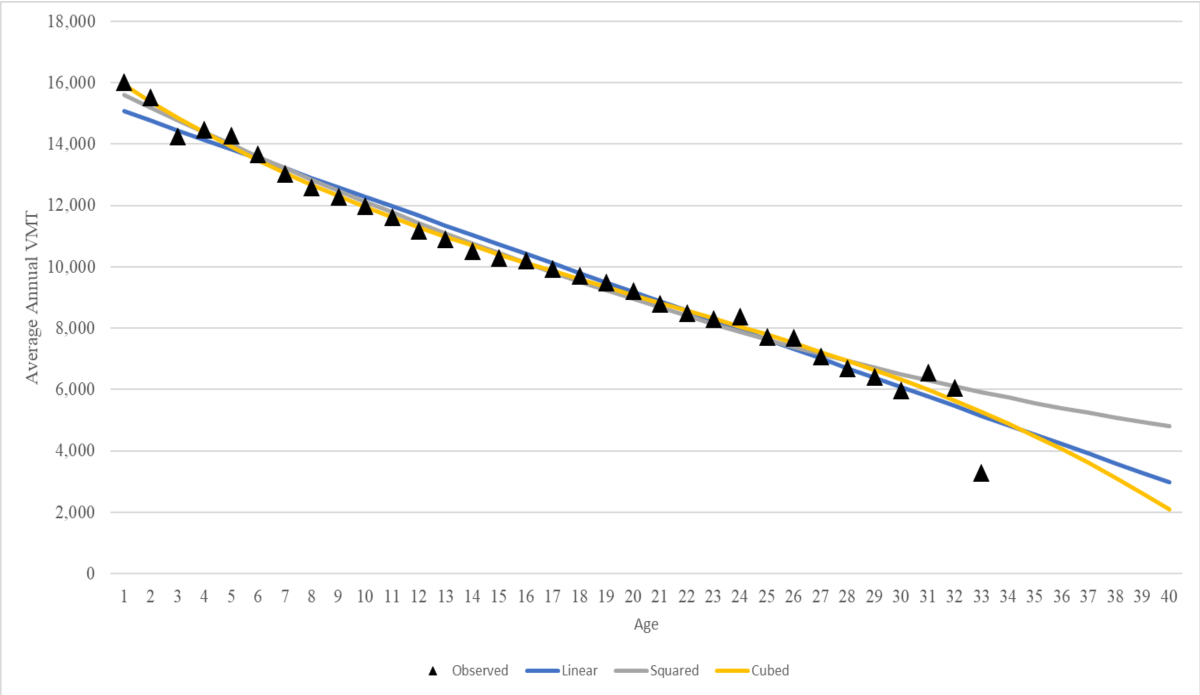


Figure 4-16 also shows that average annual VMT occasionally fluctuates at certain ages, which is likely attributable to changes in ownership. For example, average annual use declines slightly at age three and then increases at age four before resuming its gradual decline, which is probably a consequence of vehicles coming off 3-year leases with maximum permissible mileage and entering the resale market. The data are likely picking up the transfer of vehicles from their original owners to new households with higher demand for vehicles.

The agency tested several relationships to summarize the pattern of vehicle use with age. Because the CAFE Model carries no disaggregated representation of vehicle ownership or usage that would capture the variation in usage shown in Table 4-11, using the average use at each age in the regression allows the CAFE Model to capture the total VMT attributable to a model year cohort, and to benchmark against other annual estimates of light-duty VMT. Figure 4-17 shows the average usage rates for cars by age (as black triangles) as well as linear, quadratic, and cubic polynomial fits of age on these points.[793] The average usage rates follow a relatively smooth pattern but appear to decline at an accelerating rate for the oldest ages. The linear equation captures this trend for older vehicles but underestimates average use at early ages. The quadratic fit shows a diminishing decrease in the usage of older vehicles and may overestimate their use. In contrast, the cubic model accurately captures both the usage patterns at early ages and the accelerating decrease in the usage of older ages. For this reason, NHTSA selected the cubic curve as the basis for the car VMT schedules by age. The agency followed a similar process to classify mileage accumulation for other vehicle types. A cubic fit performed the best for cars, pickups, and HDPUVs. SUVs were best fit by a quadratic polynomial. The resulting annual VMT schedules based on these functions are shown in Table 4-12.

Figure 4-17: Polynomial Fits for Average Car VMT



4.3.2.3. Mileage Accumulation Schedules for the Base Year 2016

As Table 4-12 illustrates, passenger cars are driven on average slightly less than either SUVs or pickup trucks and at least through the first 10 years of use, HDPUVs are driven more than the other vehicle categories.[794] Importantly, these annual driving rates represent the estimated annual mileage accumulation of a vehicle, of a given body style, that survives to reach that age. While vehicle retirement rates are generally low across all body styles in the early years of ownership, rates accelerate with age and most of the vehicles originally

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[793] In general, the objective of a polynomial regression is to capture the nonlinear relationship between two variables. While the fit produces a nonlinear curve, it is linear in the coefficients. Choosing the lowest degree of the polynomial function that captures the inflection points in the data preserves the degrees of freedom and ensures that applying the polynomial function to observations outside the range of data (as done here for ages beyond 30) is well behaved.
[794] These same mileage accumulation schedules can also be found in the CAFE Model Input File "parameters," on the "Vehicle Age Data" tab.

produced during a model year cohort will have been retired by the time they reach age 20. Using the average construction effectively shifts some accumulated miles within the cohort – vehicle owners who drive more than the average will benefit more than we estimate from improved fuel economy, while drivers who use their vehicles less intensively will benefit less.

However, because the benefit-cost analysis does not distinguish among individual vehicles or owners, it is sufficient to capture total benefits, and this can be accomplished by representing each model year cohort and age by its annual VMT. It is also generally true that the vehicles that survive to advanced ages are not the same vehicles that were used most intensively early in their lives. Future iterations of this work will continue to improve the CAFE Model's representation of the joint relationship between utilization and retirement beyond the cohort-specific representation in this analysis.

Table 4-12: VMT Schedule by Body Style and Age

Vehicle Age	Annual Mileage Accumulation			
	Cars	Vans/ SUVs	Pickups	HDPUV
0	15,922	16,234	18,964	22,085
1	15,379	15,805	17,986	20,873
2	14,864	15,383	17,076	19,732
3	14,378	14,966	16,231	18,659
4	13,917	14,557	15,449	17,651
5	13,481	14,153	14,726	16,708
6	13,068	13,756	14,060	15,825
7	12,677	13,366	13,448	15,002
8	12,305	12,982	12,886	14,235
9	11,952	12,605	12,372	13,523
10	11,615	12,234	11,903	12,863
11	11,294	11,870	11,476	12,253
12	10,986	11,512	11,088	11,691
13	10,690	11,161	10,737	11,174
14	10,405	10,816	10,418	10,701
15	10,129	10,477	10,131	10,268
16	9,860	10,146	9,871	9,873
17	9,597	9,820	9,635	9,515
18	9,338	9,501	9,421	9,191
19	9,081	9,189	9,226	8,899
20	8,826	8,883	9,047	8,636
21	8,570	8,583	8,882	8,400
22	8,313	8,290	8,726	8,189
23	8,051	8,004	8,577	8,001
24	7,785	7,724	8,433	7,833

Vehicle Age	Annual Mileage Accumulation			
	Cars	Vans/ SUVs	Pickups	HDPUV
25	7,511	7,450	8,290	7,683
26	7,229	7,183	8,146	7,549
27	6,938	6,923	7,998	7,428
28	6,635	6,669	7,842	7,319
29	6,319	6,421	7,676	7,218
30	5,988	6,180	7,497	7,125
31	5,641	5,946	7,302	7,035
32	5,277	5,718	7,089	6,948
33	4,893	5,496	6,853	6,861
34	4,488	5,281	6,593	6,771
35	4,061	5,072	6,305	6,677
36	3,610	4,870	5,987	6,575
37	3,133	4,674	5,635	6,464
38	2,629	4,485	5,248	6,342
39	2,096	4,303	4,821	6,206

4.3.3. Using the Mileage Accumulation Schedules to Estimate Total VMT

The prior subchapter described the process for deriving mileage accumulation schedules using data through calendar year 2016. There are several reasons that vehicles' typical use at different ages, or mileage accumulation rates, could differ from those estimated using 2016 data. Fuel prices could change and thus affect the cost of operating cars and light trucks of all ages, economic growth could spur additional demand for travel and thus increase use of vehicles of some ages, or the fuel efficiency of cars and light trucks of varying ages could change over time, as new model years featuring higher fuel economy are incorporated into the fleet and older models that originally met less stringent fuel economy standards are retired. To reflect these possibilities, the agency's CAFE Model projects total VMT for future calendar years by adjusting the schedules of average annual vehicle use for the odometer data's base year (2016) to account for changes in fuel prices and fuel economy and combining the adjusted schedules with the number of vehicles of each age projected to be in use to estimate total VMT for each future calendar year.

The CAFE Model generates estimates of future VMT by calculating changes in the average cost of fuel per mile driven for cars and light trucks of each age from the 2016 odometer data to reflect conditions in each future calendar year. The age of a vehicle "cohort" during a future calendar year uniquely identifies its model year (because each cohort's age is defined as the difference between the current calendar year and the model year when it was originally produced) and thus its average fuel economy, which is assumed to remain unchanged throughout its lifetime. The CAFE Model then applies an elasticity of average annual vehicle use with respect to fuel CPM to these changes (expressed as percentages) in per-mile fuel costs (described in TSD Section 4.3.5) to estimate the resulting percent change in the average use of vehicles of each age from 2016 to each future year (this is different from the rebound effect, as explained later). Finally, these estimated percentage changes are applied to average annual driving by vehicles of each age presented in Table 4-12 to produce revised estimates of their average use in future calendar years.

The change in the average cost of fuel per mile driven between 2016 and any future calendar year (CY) for vehicles produced during model year (MY), which are then of age A = CY – MY, has two sources. The first is the difference in fuel prices between 2016 and the future year CY, which affects the per-mile cost for vehicles of all ages; they will be driven less in year CY than they were in 2016 if fuel prices have risen since 2016, and more if fuel prices have declined. Its second source is the difference in the average on-road fuel economy of vehicles produced during the model year that has reached a given age during 2016 and the fuel economy of the model year that was of that same age during 2016. Thus, the percent change in average fuel CPM for vehicles of each age between 2016 and a future calendar year is:

Equation 4-10: Full Change in Cost-Per-Mile of Travel

$$\%\Delta CPM_{SN,MY,CY} = \frac{\left(\frac{FP_{CY}}{FE_{SN,MY}} - \frac{FP_{2016}}{FE_{REF}}\right)}{\frac{FP_{2016}}{FE_{REF}}}$$

In Equation 4-10, FP_{2016} represents fuel price in dollars per gallon during 2016, FP_{CY} is fuel price during a future calendar year, and $FE_{SN,MY}$ is the average fuel economy of cars or light trucks produced during model year under the regulatory alternative or scenario SN, which will have reached a given age A during calendar year. Finally, FE_{REF} is the average fuel economy of the cars or light trucks that were of that same age during 2016. Although not indicated explicitly, Equation 4-10 applies to vehicles of each age during calendar year, since each model year represented in the fleet during a future calendar year represents vehicles of a different age, Vehicle use responds to changes in fuel prices because as Equation 4-10 above suggests, these directly affect the cost of driving each mile, a key determinant of vehicle use. Annual use of vehicles of each model year or "vintage" (and thus age) that make up a future calendar year's vehicle fleet will decline from their base year averages if fuel prices and thus the cost of driving each mile is higher than they were during 2016, the base year when the original mileage accumulation schedules were developed. Conversely, if fuel prices are lower in a future calendar year than they were in 2016, per-mile driving costs will decline and the average annual use of vehicles of each vintage and age comprising that year's fleet will increase from its average value tabulated for 2016. The response of average vehicle use to changes in fuel prices (via their effect on fuel CPM driven) is determined by the elasticity of annual vehicle use with respect to fuel price, which measures the percent change in average annual VMT resulting from a one percent change in the fuel cost of driving each mile.

Previous versions of NHTSA's CAFE Model did not incorporate the effect of future economic conditions other than fuel prices on future vehicle use. They estimated the effect of fuel prices on vehicle use by setting the elasticity of average use of all vehicle types and ages with respect to fuel price per gallon equal to the elasticity used to estimate changes in the use of new vehicles as their fuel economy improved (the fuel economy rebound effect, discussed in Chapter 4.3.5 below). In contrast, the current version of the CAFE Model estimates total vehicle travel during each future calendar year independently using a model developed to produce FHWA's official forecasts of vehicle travel, and this model includes fuel CPM as measured in Equation 4-10 above as an explanatory variable. Thus, the coefficient attached to that variable, which is estimated econometrically using historical data on vehicle use, fuel prices, and fuel economy (as well as other variables), corresponds to the elasticity of vehicle travel with respect to fuel CPM. Its estimated value is -0.085 (which corresponds to a fuel economy rebound effect of 8.5 percent), and the current CAFE Model relies on this value to adjust the base year mileage accumulation schedules to account for future changes in fuel prices from their level in 2016.[795] This value is closely comparable to the 10 percent fuel economy rebound effect the agency uses to estimate increased driving resulting from improvements in fuel economy required by the different regulatory alternatives it considers.

As Equation 4-10 shows, changes in driving costs – and thus in vehicle use – from the base year when the original mileage accumulation schedules were developed are also affected by differences between the fuel economy of cars and trucks of different ages during future calendar years and the fuel economy of vehicles that were of comparable ages during the 2016 base year. By applying the equation, the CAFE Model also

[795] Although users of the CAFE Model can still define a different value for the fuel economy rebound effect used to estimate the increase in annual use of new cars and LTs resulting from higher CAFE standards, doing so will not affect the VMT forecast generated internally by the CAFE Model or the forecast produced by FHWA's. However, it will create an asymmetry between responses to fuel price and changes in fuel economy, the size of which depends on how much the user-specified rebound effect differs from 8.5 percent. This issue is present to some extent in NHTSA's analysis supporting this final rule, since as discussed in detail in FRIA Chapter 4, that analysis employs a fuel economy rebound effect of 10 percent.

accounts for changes in the average use of vehicles of different ages during future years in response to their higher fuel economy compared to those of corresponding ages during the 2016 base year. As the fuel economy each new model year is required to achieve improves over time, vehicles of each age will be driven slightly more than their counterparts were during 2016 (as long as fuel prices remain constant), since as Equation 4-10 illustrates, their higher fuel economy translates into lower operating costs.[796]

As an extreme example, even if there were no further improvements in fuel economy for new model years after 2022, the initial year of the agency's compliance analysis, the fuel economy of vehicles of all ages making up the future fleet would continue to increase throughout much or all of the analysis period. This is because the average fuel economy of vehicles has *already* increased consistently for many model years, so that for example, vehicles that were 10 years old at the beginning of the analysis period (those produced during model year 2013, which reached age 10 during 2022) will have lower fuel economy than those reaching age 10 during 2023 and later years, which were produced in model years 2014 and later.[797]

This gradual transition toward higher fuel economy levels for model years vehicles through 2022 proceeds at exactly the same pace in each regulatory alternative the agency analyzes, since these vehicles have *already* been manufactured by the time the compliance analysis period begins in 2022. The rate at which these historical or "legacy" model years will be retired and replaced by new, higher-MPG models differs slightly among the alternatives considered, because achieving required improvements in fuel economy raises new car and light truck prices and reduces the rate at which older models are retired and replaced by new ones. The retirement and replacement of older vehicles occurs most rapidly under the No-Action Alternative and progressively more slowly under alternatives that require more rapid improvements in fuel economy, although these differences are likely to be very modest. At the same time, of course, more stringent regulatory alternatives will cause the fuel economy of the new cars and light trucks produced during future model years to increase more rapidly, so that on balance those alternatives will raise the overall average fuel economy of the fleet faster.[798]

The agency's analysis ascribes the effects on vehicle use resulting from required improvements in the fuel economy of model years after 2022 entirely to the regulatory alternatives it considers and attempts to isolate them from changes in vehicle use that occur in response to fluctuations in fuel prices and other economic conditions that are outside the realm of fuel economy regulations (i.e., "exogenous"). To do so, the CAFE Model first constructs a hypothetical measure of "non-rebound" VMT for future years that incorporates the response of driving costs and vehicle use to forecast changes in future fuel prices, and to improvements in the fuel economy of new cars and light trucks from the odometer data's base year of 2016 only through model year 2022. Increases in vehicle use from this "non-rebound" level of VMT that result from improvements in fuel economy required by each regulatory alternative the agency evaluates are ascribed uniquely and fully to that alternative. (This includes the No-Action Alternative, since even it reflects some very minor improvements in fuel economy after 2022 in response to previously adopted standards and other factors.)

The CAFE Model estimates non-rebound VMT by adjusting the 2016 base year mileage accumulation schedules using a slightly different measure of future changes in per-mile driving costs from that specified in Equation 4-10 above. Like that shown above, it includes the effects of changes in fuel prices since the base year of 2016, but it differs from Equation 4-10 by omitting the effects of fuel economy changes after 2016 from the changes in fuel CPM it calculates for future years. Equation 4-11 shows this revised measure of the change in fuel CPM for cars and light trucks of different ages during calendar year CY:

[796] For estimates of the magnitude of this elasticity, see e.g., Goodwin, P. et al. Elasticities of Road Traffic and Fuel Consumption with Respect to Price and Income: A Review. *Transport Reviews*. Vol. 24: pp. 275-92. Available at: https://www.researchgate.net/publication/32885803_Elasticities_of_Road_Traffic_and_Fuel_Consumption_with_Respect_to_Price_and_Income_A_Review/. (Accessed: Feb. 13, 2024).

[797] In practice, light-duty vehicles of the same regulatory class (cars and LTs) or body style (cars, SUVs, vans, and pickups) produced during the same model year will be retired at different rates over time, and this process can change the average fuel economy of those remaining in use. Some specific vehicle models and manufacturers have reputations for longevity and individual vehicle models with different fuel economies may seem like better candidates for repairs under particular fuel price scenarios. In light of this, the fuel economy for a given body-style will likely differ from the sales-weighted average fuel economy when the cohort was new, even without accounting for degradation and changes to the on-road gap over time.

[798] Moreover, because newer vehicles are driven more each year than older ones, the fleet's usage-weighted average fuel economy will rise more rapidly than the average MPG of the vehicles making up the evolving fleet.

Equation 4-11: Fuel Price and Secular Improvement Component of Elasticity

$$\%\Delta NonRbdCPM_{MY,CY} = \frac{\left(\frac{FP_{CY}}{FE_{MIN(2016,\ MY)}} - \frac{FP_{2016}}{FE_{REF}}\right)}{\frac{FP_{2016}}{FE_{REF}}}$$

In Equation 4-11, FP_{2016} again refers to fuel price per gallon during 2016, and FP_{CY} to fuel price per gallon during a future calendar year. As in the previous equation, FE_{REF} refers to the average FE of the model year cohort that was of age = 2016 – MY during calendar year 2016. In Equation 4-11, $FE_{MIN(2016,MY)}$ refers to the average fuel economy of cars or light trucks produced during any post-2016 MY, but this value differs from the corresponding factor in the previous equation. As its subscript *MIN(2016,MY)* indicates, it is the *lower* of the actual fuel economy of cars or light trucks that reached age = CY – MY during CY and the fuel economy of those that were of that same age during 2016. As with the previous equation, Equation 4-11 applies to vehicles of all ages during each future calendar year, again because the difference between the calendar year and a vehicle's model year determines its age.

Thus, Equation 4-11 differs from the previous equation only in the respect that in Equation 4-10 the fuel economy in the denominator of the first term is the *actual* fuel economy of each (post-2016) model year being evaluated, while in Equation 4-11 it is the *minimum* of that value and the fuel economy cars or light trucks achieved during model year 2016. In effect, Equation 4-11 assumes that no improvements in fuel economy would have occurred after model year 2016, but at the same time the fuel economy of cars and light trucks produced during more recent model years would not be allowed to fall *below* their levels of model year 2016. This assumption implies that fuel economy improvements through model year 2016 *will* be accounted for when calculating non-rebound VMT for any later calendar year, but that further increases in fuel economy after model year 2016 *will not* be. Thus, increases in average annual VMT per vehicle during calendar years after 2016 would reflect only subsequent changes in (inflation-adjusted) fuel prices.

Conversely, changes in average annual VMT per car or light truck would reflect increases in the fuel economy of future cars and light trucks from the levels they achieved during model year 2016 (again, via the fuel economy rebound effect).[799] The agency's analysis ascribes the effects of post-model year 2016 improvements in fuel economy on fuel costs and vehicle use – and thus on fuel consumption, emissions, safety, and other consequences of vehicle use – to the regulatory alternatives it considers. Following this approach means that there will be some additional VMT attributable to the fuel economy rebound effect in future years even under the No-Action Alternative used in the analysis. This occurs because the actual fuel economy of new cars and light trucks will increase after model year 2016 under the No-Action Alternative due to previously-adopted increases in CAFE standards for later model years, efforts by manufacturers who under-complied with prevailing standards during earlier model years to "catch up" with standards for later years, and any voluntary overcompliance by manufacturers with standards prevailing after model year 2016.

Combining the adjustments to average annual VMT during the reference year of 2016 for different light-duty vehicle body styles (cars, SUVs/vans, and pickups) of each age from Equation 4-11 with the estimated populations of vehicles of different ages in use during a future calendar year produces an initial estimate of non-rebound VMT, as shown by Equation 4-12:

Equation 4-12: Unadjusted Total Non-Rebound VMT in a Future Calendar Year

$$NonReboundVMT_{CY} = \Sigma_{A}^{Ages} \sum_{S}^{Styles} VMT_{A,S} \cdot (1 + \%\Delta NonRbdCPM_{MY,CY} \cdot \varepsilon) \cdot Population_{CY,A,S}$$

where $VMT_{A,S}$ represents average annual mileage for light-duty vehicles of age A and body style S during the base year of 2016, $\%\Delta NonRbdCPM_{MY,CY}$ is the percent change in fuel CPM resulting from the difference in fuel price between CY and the base year of 2016 for vehicles of model year (which have reached age A=CY-

[799] NHTSA intends to update this reference year the next time the agency acquires an update to the database of odometer readings.

MY), $Population_{CY,A,S}$ is the number of vehicles of that age and body type estimated to remain in service during a future calendar year, and ε is the elasticity of annual vehicle use with respect to fuel CPM driven (derived from FHWA's VMT forecasting model, and equal to -0.085). Because both the adjusted value of annual VMT for vehicles of age A and the number of them in use ($Population_{CY,A,S}$) both vary by regulatory alternative, the CAFE Model generates a slightly different estimate of NonReboundVMT during each future calendar year under each alternative; however, we omit the subscript corresponding to regulatory alternatives from Equation 4-12 for simplicity.

Factors other than fuel costs can also affect households' and businesses' demands for vehicle travel, even if fuel prices remain constant throughout the analysis period and fleetwide fuel economy improves only minimally as a consequence of continuing fleet turnover (as it does in the "non-rebound" case), and total VMT could still vary in response to changes in these other factors. Not only could the forecast of non-rebound VMT continue to grow under appropriate conditions, but it might actually do so at a faster rate than Equation 4-12 predicts – for example, because of unusually rapid population growth -- since that equation incorporates only the effects of fleet turnover on fuel economy, fuel costs, and vehicle use. Conversely, events such as recessions could depress actual VMT below levels estimated using Equation 4-12, as occurred for example during the Great Recession in 2008-2009.

To ensure that the CAFE Model's estimates of light-duty VMT for future years are also broadly consistent with demographic growth and economic conditions other than fuel prices, the agency constrains non-rebound VMT under each regulatory alternative – including the No-Action Alternative used to analyze future CAFE standards – to match an independent forecast based on demographic trends and aggregate economic growth. As described in more detail below, it uses a travel forecasting model developed and used by FHWA to produce a forecast of growth in car and light truck use that is consistent with the same forecasts of population growth, increases in household formation, growth in aggregate economic output and personal income, and consumer confidence used elsewhere throughout its analysis.

In the case of the HDPUV market, a separate forecast of vehicle use is not readily available. The FHWA forecast used to constrain the light-duty fleet appear to include most HDPUVs, but may omit some HDPUV models, and could also include others that fall outside the HDPUV classification. The agency continues to pursue potential methods to forecast aggregate VMT separately for HDPUVs. For the analysis in this final rule, forecast HDPUV mileage relies solely on the bottom-up approach described above and no constraining procedure like that used for light-duty vehicles is applied.

4.3.4. Constraining VMT in the CAFE Model

The process described in the previous subchapter of building up a forecast of total VMT using the adjusted mileage accumulation schedules produces modest differences among alternatives. These differences result from alternatives having a different effect on new vehicle sales and retirement of existing vehicles, which vary in proportion to required improvements in fuel economy. Although the amount of rebound effect driving under each alternative can be estimated accurately, much of the VMT that is "lost" when sales of new vehicles decline is likely to be replaced by increased use of older models, and the change in fleetwide VMT from this latter effect is much more difficult to estimate reliably.[800]

In response to this challenge, NHTSA's analysis calculates the increased use of new vehicles under each alternative under consideration by applying its estimate of the rebound effect (which it derives as described below) to the increase in fuel economy each alternative requires. The agency then assumes all travel that would have taken place in new vehicles "not sold" under each alternative will be replaced by increased driving of used vehicles; the specific procedure used to reallocate this "lost" VMT is described in detail below. This assumption is likely to overestimate total vehicle use (by a progressively larger margin for more stringent alternatives), because the combination of higher vehicle prices and lower fuel costs would be expected to reduce aggregate travel demand, but the agency believes this effect is likely to be small, particularly in comparison to the increase in driving caused by the fuel economy rebound effect.

[800] In fact some travel demand could also shift to substitutes like public transit in response to a change in sales of new vehicles and scrappage of older vehicles.

To implement this assumption, before applying the rebound effect the CAFE Model constrains each year's "non-rebound" forecast of light-duty vehicle use under the reference baseline and each regulatory alternative to match annual values projected using the FHWA's VMT forecasting model, regardless of differences the model simulates among alternatives in the size or age distribution of the light-duty fleet. In future years where total VMT calculated internally by the CAFE Model differs from the FHWA forecast, each age or model year cohort's average VMT is adjusted up or down so that the two estimates match. In calendar years where the CAFE Model's estimate of total VMT constructed using average mileage by vehicle age and the numbers of vehicles of different ages is below the forecast from the FHWA model, the CAFE Model's estimates of annual VMT for cars and trucks of each age are adjusted upward by the proportion necessary for its forecast to match that produced by the FHWA model. Conversely, if the initial estimate of total VMT for a calendar year the CAFE Model develops using its fleet size and age distribution in conjunction with mileage accumulation schedules for cars and light trucks exceeds that forecast by the FHWA model, average use of vehicles of each age is scaled down proportionally until the two estimates match. This process ensures that any differences in total VMT among regulatory alternatives reflect only the different levels of fuel economy they require and their consequences for car and light truck use via the fuel economy rebound effect. However, no such adjustment is applied to the forecast of HDPUV VMT generated within the CAFE model, partly for the practical reason that no external forecast is available to use as a constraint, and partly because it seems more plausible that vehicle use for work-related purposes, the primary use of HDPUVs, would vary among alternatives.

FHWA's VMT forecasting model is based on underlying theories of the determinants of travel demand, with their parameters estimated econometrically from annual time-series data on vehicle use, demographic variables, and measures of aggregate economic output and income. It employs an auto-regressive distributed lag specification including error correction terms in an effort to capture the long-run behavioral relationships between vehicle use and economic and demographic growth, as well as the year-to-year adjustments of vehicle use to short-term fluctuations in economic activity. Full documentation of its development, calibration, and use is available from FHWA, and the model is described only briefly here.[801] As FHWA has revised the model to improve its forecasting performance, updated versions have been fully integrated into NHTSA's CAFE Model. Table 4-13 reports the variables currently included in FHWA's light-duty VMT forecasting equation and the most recently estimated values of their coefficients.[802]

Table 4-13: FHWA VMT Forecasting Model

Adjustment Variable	
Previous Period VMT	-0.358 (0.048) ***
Long-Run Variables	
Personal Disposable Income PC	3.567 (0.468)**
Personal Disposable Income PC Sq.	-0.435 (0.072)**
Fuel Cost per Mile	-0.085 (0.018)***
Short-Run Variables (First Differenced, except Consumer Confidence)	
Personal Disposable Income PC	3.661 (0.812)*
Personal Disposable Income PC (-1)	-0.310 (0.075)***
Personal Disposable Income PC (-2)	-0.249 (0.069)*
Personal Disposable Income PC Sq.	-0.547 (0.124)*
Consumer Confidence	0.046 (0.014)***

[801] Pickrell, D. et al. 2020. FHWA Travel Analysis Framework: Development of VMT Forecasting Models for Use by the Federal Highway Administration. Department of Transportation, Volpe. pp. 1-19. Available at: https://www.fhwa.dot.gov/policyinformation/tables/vmt/vmt_model_dev.pdf. (Accessed: Feb. 13, 2024).
[802] The 90 percent confidence interval for the estimated coefficient on fuel cost per mile easily includes -0.10, which corresponds to the 10 percent rebound effect the agency uses throughout its analysis.

Structural break Indicator (2006)	-0.036 (0.007)
Constant	0.435 (0.266)
Observations	50
Adj. R2	0.88
RMSE	0.007
Cumby-Huizinga Test for Autocorrelation (P-Value (One Lag))	0.69
Bounds F-Stat.	19.34***
Bounds T-Stat.	-7.43***
In-Sample MAPE (1970-2019)	0.49%
Out-of-Sample MAPE (2014-2019)	0.85%
Notes: Suffixes on the variable names indicate the values of a variable from the previous year (-1) period two years previous (-2). Critical values for the bounds test are taken from Pesaran et al. (2001) for case 3. Model lag lengths were based on best Bayesian Information Criterion statistic.	
Standard errors in parentheses: † p<0.1 * p<0.05 ** p<0.01 *** p<0.001	

As indicated above, before applying the rebound effect NHTSA's analysis constrains each future year's VMT under all regulatory alternatives to match the forecast of VMT produced by the FHWA model. It does so by adding or subtracting VMT from the provisional forecast for each future year that was previously generated using Equation 4-12. The increment of VMT added or subtracted, denoted $\Delta Miles_{CY,Alt}$ in Equation 4-13 below, is simply the difference between each calendar year's forecast of total VMT derived from the FHWA model and the estimate of total VMT obtained previously from Equation 4-12. That is:

Equation 4-13: Difference Between VMT Constraint and Unadjusted Non-Rebound VMT

$$\Delta Miles_{CY,Alt} = VMTConstraint_{CY} - NonReboundVMT_{CY,Alt}$$

Over time, each regulatory alternative results in a slightly different size and composition of the on-road car and light truck fleet, including the number of vehicles of each type remaining in use, the model years when they were originally produced (and thus their age distribution), and the average fuel economy of each model year and age. As a consequence, the total unadjusted VMT in each calendar year given by Equation 4-12 will also differ slightly among regulatory scenarios. Because the forecast of total VMT from the FHWA model will be the same under each alternative, Equation 4-13 shows that $\Delta Miles_{CY,Alt}$ will differ for each regulatory scenario as a result. By distributing $\Delta Miles_{CY,Alt}$ across the vehicle fleet in each calendar year, the CAFE Model scales unadjusted non-rebound VMT to equal the same adjusted level under each regulatory alternative.

While several different methods could have been used to reallocate $\Delta Miles_{cy,Alt}$ across the on-road fleet to preserve the non-rebound VMT constraint, the CAFE Model applies one of the simplest. Lacking empirical evidence about how these additional miles should be distributed across the vehicle population (which would require data showing how the distribution of VMT has shifted among body styles and vehicles of different ages over time), a simple approach seemed the most sensible. Under reasonable assumptions about model inputs, the magnitude of $\Delta Miles_{cy,Alt}$ is relatively small for most body types and ages – at most a few hundred miles per year, for vehicles that typically average 10,000 miles or more per year.[803]

[803] A notable exception to this is the impact of the COVID pandemic on total light-duty vehicle sales and VMT, both of which dropped precipitously during 2020 in response to both economic distress and mandated travel restrictions, and the structure of NHTSA's forecasting models causes these declines to persist through the early years of the forcast period.

The primary goal of reallocation is to adjust total non-rebound VMT so that it reflects the FHWA model-based forecast of total VMT in every calendar year and for each regulatory alternative. At the same time, it is important that any reallocation preserve the general pattern of declining average mileage with age apparent in the reference mileage accumulation schedule from 2016, since that represents the agency's best estimate of observed usage at the outset of the analysis and the pattern of declining use with age has long been observed. In particular, the reallocation approach preserves the basic ideas that annual mileage declines with vehicle age because newer (and more fuel-efficient) vehicles are used more intensively than their older counterparts, and that annual mileage accumulation rates vary among vehicles of different body styles.

To perform this reallocation, the CAFE Model computes a ratio that varies by calendar year and regulatory alternative. The resulting ratio is then used to scale the unadjusted miles from Equation 4-12, so that the new sum of annual (non-rebound) VMT across all vehicles comprising the on-road fleet equals the total forecast for that year generated by the FHWA model. Conceptually, the constraint represents demand for motor vehicle travel in each future calendar year absent the contribution to increased VMT from fuel economy improvements occurring after model year 2016. In each regulatory alternative, for a future calendar year *CY* and body style *S*, the scaling ratio *R* is computed as:

Equation 4-14: Scaling Factor to Reallocate Non-Rebound VMT

$$R_{CY}=\frac{\Delta Miles_{CY}}{NonReboundVMT_{CY}}$$

In Equation 4-14 $\Delta Miles_{CY}$ is calculated using Equation 4-13, while $NonReboundVMT_{CY}$ is obtained from Equation 4-12. Then total adjusted non-rebound VMT is calculated as:

Equation 4-15: Total Adjusted Non-Rebound VMT

$$AdjNonReboundVMT_{CY}=\sum_{A}^{Ages}\sum_{S}^{Styles}NonReboundVMT_{CY.A,S}*(1+R_{CY})$$

While other schemes could be used to reallocate VMT across the vehicle fleet (for example, a uniform approach that either adds or removes the same number of miles from each age cohort), the scaling approach described here has several advantages. The newest model years (lowest ages) are affected the most by the constraint – mileage for all ages is scaled in proportion to unadjusted VMT, and the CAFE Model cannot add or remove large amounts of VMT in age cohorts having small numbers of vehicles or contributing small quantities of VMT to the total, so it produces stable results. By employing the scaling ratio rather than another method, we ensure that the model is robust to the widest possible array of input assumptions.

To make each alternative match the overall VMT constraint, the CAFE Model first combines the product of average mileage during the reference year for each body style and age with the value of *%ΔNonRbdCPM* calculated from Equation 4-11 and the elasticity of annual vehicle use with respect to fuel cost derived from the FHWA forecasting model. It then applies the appropriate scaling ratio derived from Equation 4-14. Unlike much of the CAFE Model's accounting, which focuses on the fuel consumption, emissions, and other impacts generated by a model year cohort over its entire lifetime, the rebound constraint and any mileage reallocation are inherently *calendar year* concepts. This reallocation occurs every calendar year, so vehicles of each model year cohort are likely to experience many such reallocation events – most positive, but some potentially negative – over the course of their lifetime in the fleet.

As other elements of this analysis show, there are two primary reasons why raising CAFE standards causes travel demand to be redistributed within the on-road fleet. First, different alternatives cause the composition of the fleet to evolve differently over time while the constraint ensures that changing fleet size does not influence aggregate travel, and this combination requires some redistribution of travel among vehicles of different ages. Each alternative also produces a fleet of a slightly different total size (number of vehicles), a specific age distribution, and a unique pattern of variation in fuel economy (and thus fuel costs) with the age and body-style of vehicles comprising it.

These differences are direct consequences of differences in CAFE stringency that influence the number of new vehicles sold each year, the fraction of them that are sold as different body styles, the likelihood that used vehicles of various ages will be retired each year, and the fuel economy of each model year cohort making up that year's on-road fleet. However, these factors do not influence aggregate demand for VMT in the CAFE model, except for the relatively minor differences caused by the response of driving to the fuel economy rebound effect.

To derive the average fuel economy of the car and light truck fleet under the VMT constraint, the CAFE model simply allows the vehicle fleet to evolve as a consequence of newly sold vehicles entering service and normal retirement of used vehicles, while holding the fuel economy of new model years entering the fleet constant at the levels they achieved during model year 2016. Thus, as the fleet evolves over time, its overall average fuel economy slowly improves toward the fuel economy that new vehicles achieved in model year 2016, while fuel economy improvements to new vehicles occurring after model year 2016 are excluded from the projection of non-rebound VMT. This isolates the effects of fleet turnover and changes in future fuel prices on projected travel demand from those of requiring higher fuel economy.

Increases in vehicle use and its consequences that result from required improvements in fuel economy after model year 2022, the base year used for this analysis, are assigned to the individual regulatory alternatives this analysis considers. Because the increases in fuel economy for model years 2017-2026 under each regulatory alternative—including the No-Action Alternative—result from previously established standards (plus any voluntary overcompliance with those standards), those increases are identical under each regulatory alternative. Again, the purpose of isolating the effects of improved fuel economy from those of changes in fuel prices and normal fleet turnover is to ensure that differences in VMT among regulatory alternatives reflect variation in the levels of fuel economy they require.

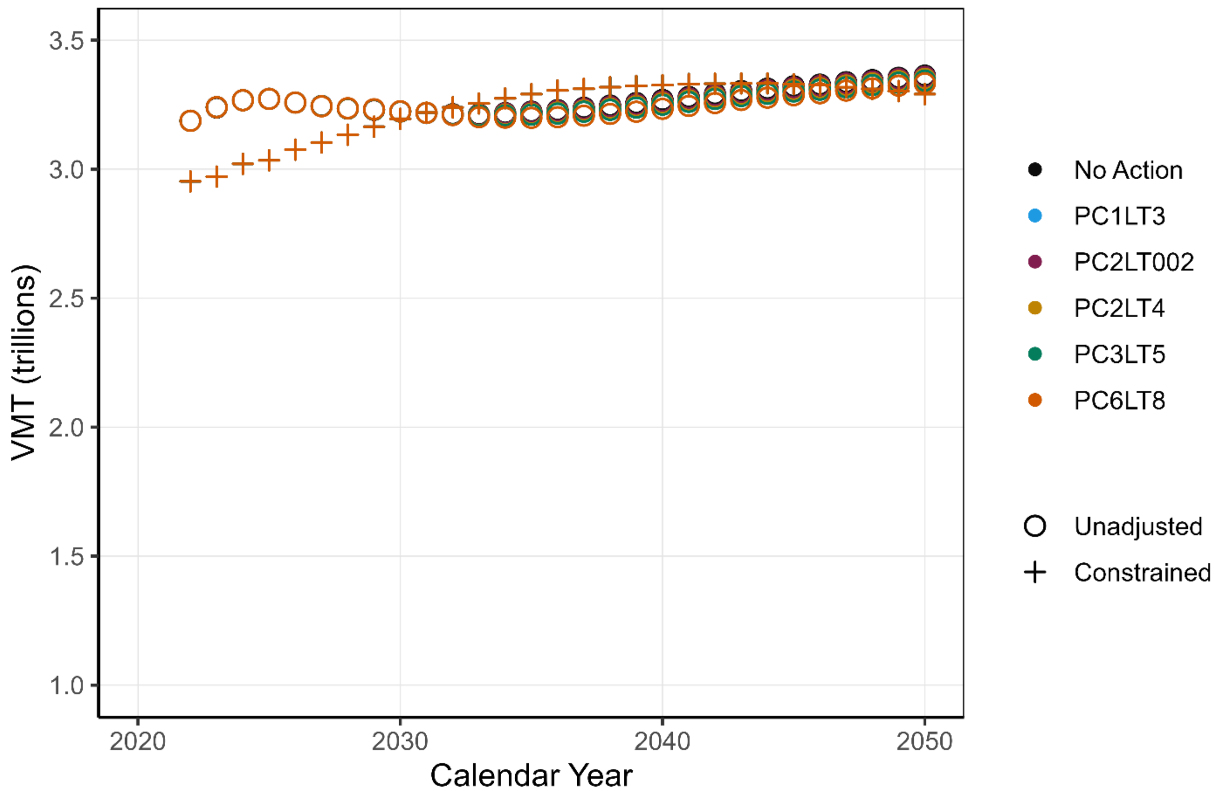
Although this distinction implies that some rebound-related increase in vehicle use occurs even in the No-Action Alternative – partly as a consequence of more stringent standards across multiple programs – those non-CAFE programs affect each of the action alternatives under CAFE as well, so any rebound-effect travel attributable to fuel economy gains required under those other programs nets out when comparing across alternatives. Aggregate travel demand is constant across scenarios until we account explicitly for the fuel economy rebound effect, and that demand must be met by the available on-road fleet.

However, the CAFE Model simulates slightly different on-road fleets under each regulatory alternative, and these differences accumulate over time. Different alternatives' fleets may differ in both their total size and in the age distribution of vehicles comprising them, each of which has important consequences for the intensity with which vehicles of different ages are used to satisfy overall demand for travel. Vehicles of different ages making up each future year's on-road fleet are only imperfect substitutes for one another, and the services they provide are not completely interchangeable. Although in theory a modestly larger number of relatively new vehicles could compensate for a significantly reduced number of older vehicles (because those new vehicles would be driven more intensively than older ones), a fleet that is *both* older and smaller is likely to likely require higher annual driving rates for all age or model year cohorts to meet the same demand for travel.

The second reason why the model redistributes VMT across the on-road fleet is a discrepancy between unadjusted VMT (the product of average annual vehicle use and the on-road vehicle population) and forecasted non-rebound VMT. In most cases, this redistribution is small in scale and fluctuates between adding and removing miles in any given year. However, in this analysis, the constrained annual VMT is strongly affected by the COVID pandemic. As shown in the figures that follow, this is most evident in the early years of the simulation and the effect is relatively small during the regulatory period. Consequently, this redistribution more often *removes* miles from the unadjusted annual VMT than it adds to them to preserve the non-rebound VMT constraint, and this downward adjustment is particularly pronounced in the early years of the agency's analysis.

As Figure 4-18 shows, the unadjusted VMT—based on the simple product of the VMT schedule (by body style and age) and the on-road vehicle population—exceeds the FHWA-based forecast of aggregate VMT prior to calendar year 2030 and dips slightly below the FHWA-based forecast through most of the remaining analysis period. Were the dip in the early years of the FHWA forecast (which is caused by the COVID-19 pandemic) not present, it seems likely that the redistribution would be *adding* rather than removing VMT throughout the period to preserve the constraint.[804]

Figure 4-18: Comparison of Unadjusted and Constrained VMT in the CAFE Model

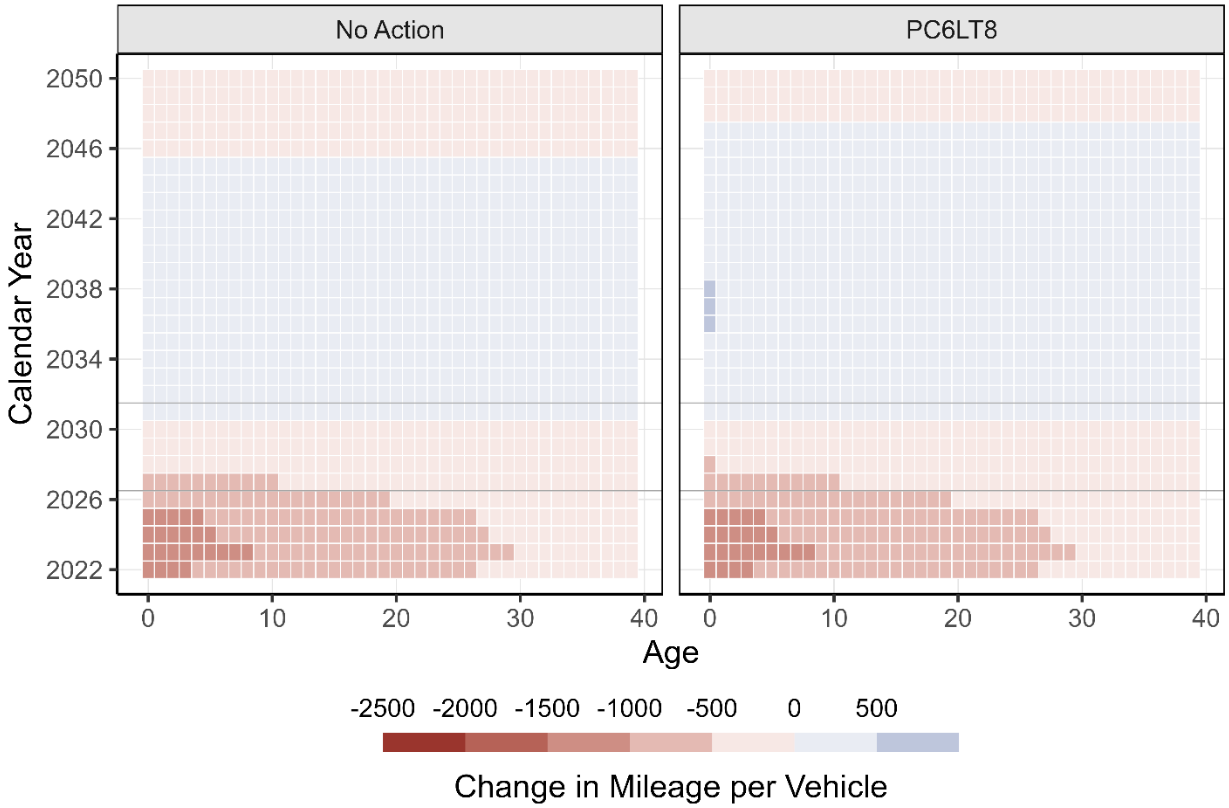


However, as a consequence of the calculated discrepancy between the VMT constraint and unadjusted VMT in the early years of the analysis, the redistribution process must aggressively remove miles from the unadjusted VMT estimate during the early years of the analysis period. While the earliest years (especially 2022 and 2023) reflect the depth and recovery related to the pandemic, the two estimates converge by 2030, after which the adjustments to individual age cohorts' average use become insignificant. Figure 4-19 illustrates the adjustments that are necessary to enforce the VMT constraint for a representative passenger car in the No Action alternative and Alternative PC6LT8; adjustments for the other alternatives look similar, but those shown in the figure represent the bounding cases. Consistent with the objective of the reallocation process, the largest absolute adjustments (in miles per year) are concentrated in age cohorts represented by larger numbers of vehicles and characterized by higher average usage, which thus make larger contributions to total VMT. As illustrated in Figure 4-18, the alternatives only begin to diverge after calendar year 2033.

The CAFE Model distinguishes among car body styles, SUVs, and pickup trucks for the purposes of simulating vehicle usage, and the VMT adjustments occur at that level as well. The reallocations are consistent across body styles and represent a reduction of about 8 percent of per-vehicle VMT in calendar year 2022. The reduction drops to less than 1 percent in 2030. As Figure 4-18 suggested previously, there are also some years where the CAFE Model is forced to add miles to the unadjusted VMT in Alternative PC6LT8 to preserve the VMT constraint, although those additions are similarly small; reallocation increases mileage by two to three percent in 2040.

[804] This would not have been a surprising result, because as discussed previously FHWA's forecast appears to include VMT for at least part of the HDPUV fleet, while the CAFE model's internally generated forecast of total VMT includes light-duty vehicles only and should thus be consistently lower.

Figure 4-19: Enforcing the VMT Constraint by Adjusting VMT



4.3.5. Accounting for the Fuel Economy Rebound Effect

The last step in the process of estimating the number of miles driven by cars and light trucks of different ages during each year of the analysis period is to account for the effect of higher fuel economy on vehicle use. As indicated previously, the agency's evaluation attributes all impacts of requiring higher fuel economy to each of the regulatory alternatives that do so, including changes in vehicle sales, retirement of used vehicles, and the lifetime use of vehicles produced during the model years that are subject to each alternative. The processes for constraining and reallocating mileage described above are intended to assign the consequences of changes in the size and composition of the car and light truck fleets to the various regulatory alternatives, while the consequences of improved fuel economy for vehicle use – the rebound effect – are estimated directly.

The fuel economy rebound effect, one example of the well-documented energy efficiency rebound effect for energy-consuming capital goods, refers to the tendency of motor vehicles' use to increase when their fuel economy is improved and the CPM of driving declines as a result. Establishing more stringent CAFE standards than the reference baseline level will lead to higher fuel economy for new cars, light trucks, and HDPUVs, thus reducing the amount of fuel consumed in driving each mile. The resulting decline in the cost to drive each mile will prompt an increase in the number of miles new cars and light trucks are driven, and this increase in vehicle use represents the fuel economy rebound effect.

NHTSA recognizes that the value of the rebound effect has an important influence on the costs and benefits associated with establishing higher CAFE standards, as well as the estimates of fatalities and injuries projected to occur under various regulatory alternatives. A larger rebound effect also reduces many of the environmental benefits associated with increased fuel efficiency. For these reasons, NHTSA staff conducted an extensive review of recent estimates of the fuel economy rebound effect, covering the past decade and spanning different geographic regions. In contrast to the agency's previous extensive reviews, which mainly compiled different authors' single "best" or most likely estimates of its magnitude, this most recent survey included all estimates of the rebound effect reported in each published study while also recognizing the often-wide uncertainty surrounding these estimates. The agency also reviewed previous surveys of published estimates of the rebound effect in order to compare their findings to its own most recent analysis.

Formally, the fuel economy rebound effect is defined as the elasticity of vehicle use with respect to vehicle fuel economy (distance traveled per unit of fuel consumed, such as miles per gallon) or fuel efficiency (fuel consumed per unit of distance traveled, such as liters per kilometer). Some research attempts to estimate this parameter directly by analyzing the relationship of vehicle use to variation in vehicles' fuel economy or fuel efficiency, while controlling separately for fuel prices. Because sources of exogenous or independent variation in fuel economy or efficiency are rare and their average values for an entire vehicle fleet change very slowly over time, many analysts instead estimate the elasticity of vehicle use with respect to fuel cost per unit of distance driven (dollars per mile, for example) and assume that this parameter is identical to the fuel economy rebound effect. In effect, this assumes that vehicle use responds identically to changes in fuel CPM regardless of whether those result from variation in fuel prices or changes in fuel economy.

The agency's survey included examples of published studies that rely on each of these strategies. Within each category, the survey identified studies that estimate the rebound effect using national aggregate time-series data on vehicle use and fuel economy or fuel cost per unit of distance traveled, average values of these variables for geographic units (nations, provinces, or states) measured repeatedly over successive years, and estimated use and fuel economy or fuel cost for samples of vehicle-owning households or of individual vehicles themselves. Each of these data sources and measurement methods involves significant empirical and statistical challenges, but each also offers important advantages for obtaining reliable estimates of the rebound effect.

Table 4-14: Summary of Recent Studies of the Rebound Effect for Light-Duty Vehicles

Study Details	Explanatory Variable	Nation		Vehicle Use Data Type			
		U.S.	Other	National Time Series	Panel of Geographic Sub-units	Household Sample	Vehicle Sample
Number of studies	Fuel economy or efficiency	7	6	1	0	3	9
	Fuel cost per mile or km	14	5	4	5	2	8
Number of estimates	Fuel economy or efficiency	27	35	2	0	31	29
	Fuel cost per mile or km	115	28	26	52	14	51
Mean estimates	Fuel economy or efficiency	16%	22%	-15%	–	15%	26%
	Fuel cost per mile or km	18%	8%	19%	22%	15%	16%

Table 4-14 summarizes the details of studies of the rebound effect NHTSA included in its updated survey, and Table 4-15 identifies the individual studies and reports their locations, time periods they span, and type of data they utilize. As indicated previously, the agency's survey included all estimates of the rebound effect reported in each published study, rather than a single best or most representative estimate. We weighted each published study equally, however, so that each individual value reported in a study that included a large number of alternative estimates received less weight than those from a study reporting a smaller number of estimates. Thus, for example, each value from a study that reported ten separate estimates was weighted only half as heavily as each value reported in a study that produced only five different estimates.

To recognize the statistical uncertainty surrounding each study's findings, the agency combined econometric estimates of the magnitude of the rebound effect with the standard errors accompanying each estimate to simulate a probability distribution for each published estimate.[805] It then compiled these into summary

[805] Some estimates of the rebound effect are mathematical combinations of two or more different parameters that are estimated econometrically; for example, the rebound effect calculated from time-series models that include a lagged value of vehicle use as an explanatory variable depends on the estimated coefficients of both fuel economy (or fuel cost per distance traveled) and the lagged value of vehicle use. In some of these cases, the standard error of the calculated rebound effect can be calculated directly using the reported standard errors of its separate parameters. In those where it could not, the distribution of rebound effect values was simulated using repeated draws (1,000) from the probability distributions of its separate parameters, and its standard error was approximated using the standard deviation calculated from that resulting distribution.

probability distributions representing different definitions of the rebound effect and the various data sources and analytic approaches used toot estimate it.

Table 4-15: Details of Recent Studies

Authors (Date)	Nation	Time Period	Data	Range of Estimates
Greene (2010)	U.S.	1966-2007	National aggregate VMT	0-13%
Wang *et al.* (2012)	Hong Kong	1993-2009	Year-to-year changes in nationwide driving	45%
Stapleton *et al.* (2016, 2017)	U.K.	1970-2012	National aggregate VMT	11-30%
FHWA (2018)	U.S.	1966-2016	National aggregate VMT	14%
Small and Van Dender (2007)	U.S.	1967-2004 2001-2004	Annual VMT for individual U.S. states	22-34% 11-32%
Barla (2009)	Canada	1990-2004	10 Canadian provinces over 15 years	17-19%
Hymel et al. (2010)	U.S.	1966-2009	Annual VMT for individual U.S. states	13-25%
Anjovic and Haas (2012)	6 EU nations	1970-2007	6 EU nations over 38 years	44%
Hymel and Small (2015)	U.S.	1966-2009 2000-2009	Annual VMT for individual U.S. states	16-25% 4-18%
Feng et al. (2013)	U.S.	1996-2000	U.S. households	2-12%
Liu (2014)	U.S.	2009	1,420 Washington, D.C. households	39-40%
Wang and Chen (2014)	U.S.	2009	105,000 households	-20 to 70%
Dillon et al. (2017)	California	2009	3,500 households	1-18%
DeBorger (2016)	Denmark	2001-2011	23,000 households	5-12%
Andersson *et al.* (2019)	Sweden	2006-2012	29,000 households	2-34%
Waddud (2009)	U.S.	1984-2003	U.S income quintiles	1-25%
Su (2011)	U.S.	2009	45,000 household vehicles	3-20%
Su (2012)	U.S.	2009	45,000 household vehicles	11-19%
Frondel *et al.* (2012)	Germany	1997-2009	2,165 households	42-59%
Linn (2013)	U.S.	2001, 2009	230,000 household vehicles	23-66%
Weber and Farsi (2014)	Switzerland	2010	8,000 household vehicles	19-81%
Gillingham (2014)	California	2001-2009	5 million vehicles	22-23%
Su (2015)	U.S.	2009	45,000 household vehicles	9-17%
Gillingham et al. (2015)	Pennsylvania	2000-2010	7 million vehicles	8-15%
West *et al.* (2015)	U.S.	2009	166,000 new vehicles	0%
Langer *et al.* (2017)	Ohio	2009-2013	229,000 driver-months	11-15%
Wenzel and Fujita (2018)	Texas	2005-2020	32 million vehicles	0-40%
Knittel and Sandler (2018)	California	1996-2010	76 million vehicles	10-25%
Roth (2019)	Switzerland	1998-2010	72,000 vehicles	0-5%

Figure 4-20 displays the resulting probability distribution of estimates of the rebound effect derived from the elasticity of vehicle use with respect to fuel economy or fuel efficiency; it incorporates results from 12 separate published studies that report a total of 70 estimates. The figure shows the distribution of all estimates over the range from 0-30 percent, together with separate distributions for studies from the United States and other nations, as well as for those relying on households' combined use of the vehicles they own and on the use of individual vehicles. Multiple "peaks" in most of these distributions are evident, often reflecting the clustering of a single study's estimates, and at other times indicating the limited number of estimates they summarize. As Figure 4-20 illustrates, the most likely estimate for the United States falls in the 15-20 percent range, while values from approximately 6-12 percent appear most likely in studies from outside the United States. The most probable estimates from both household- and vehicle-based studies also appear to fall into approximately the 6-12 percent range.

Figure 4-20: Probability Distribution of Rebound Effect Estimates Based on Fuel Economy or Fuel Efficiency

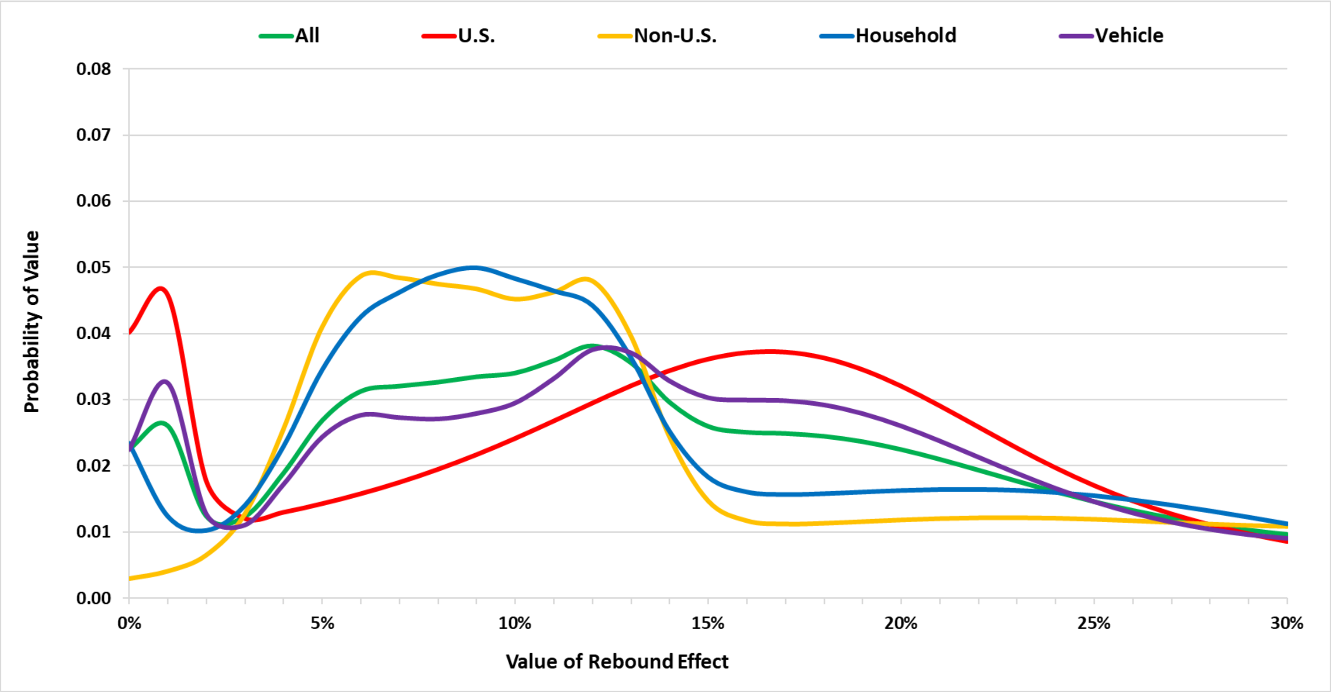
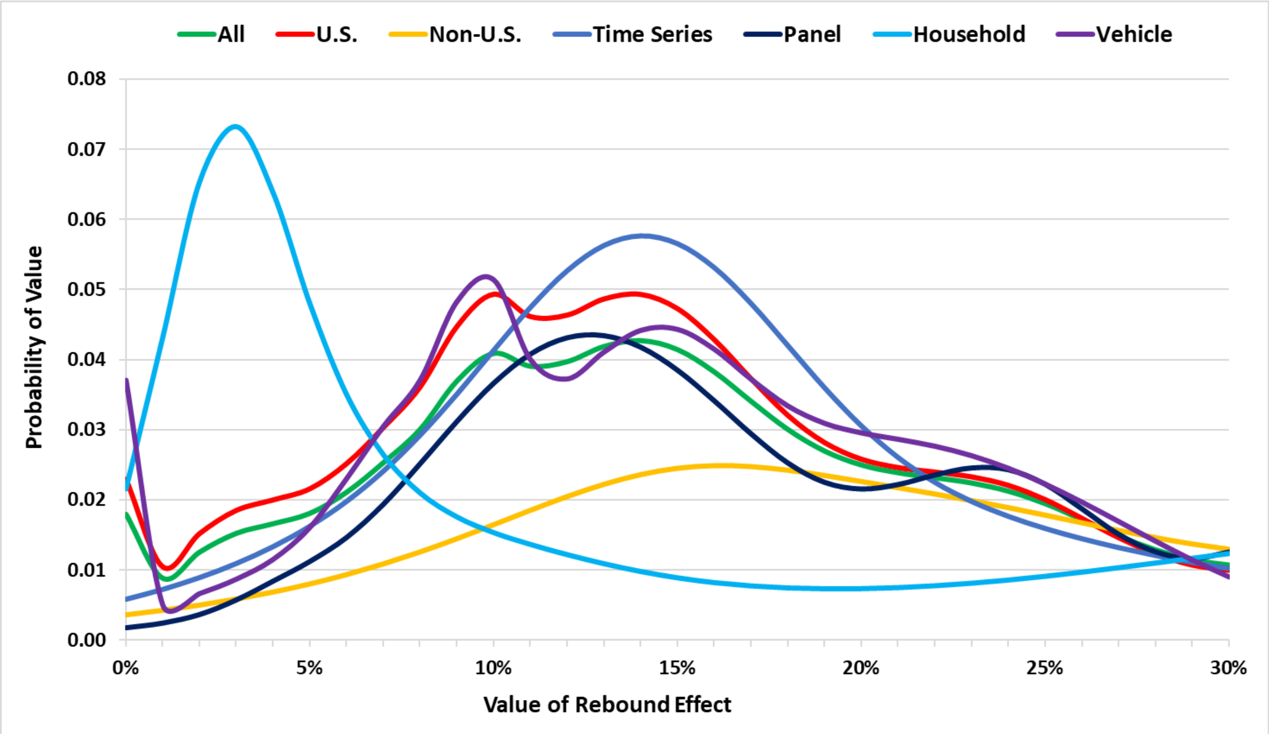


Figure 4-21 displays the probability distribution of estimates of the rebound effect derived from the elasticity of vehicle use with respect to fuel cost per unit of distance traveled. It incorporates results from 19 published studies reporting a total of 143 estimates, more than twice the number included in Figure 4-20. As it shows, the two studies relying on household vehicle use suggest most likely values for the rebound effect of less than 5 percent, while studies using other types of data and measurement approaches consistently indicate most likely values in the 10-15 percent range. Estimates for the United States show a most likely value in this latter range as well, while the distribution of non-U.S. estimates suggests a central tendency of 15-20 percent but is so "flat" by comparison that values outside this range are only slightly less likely.

Figure 4-21: Probability Distribution of Rebound Effect Estimates Based on Fuel Cost per Distance Traveled



NHTSA believes it is also important to benchmark the findings from its analysis against previous large-scale surveys of published research on the rebound effect, and Table 4-16 summarizes the findings from four such surveys. In the earliest, Greening, Greene, and Difiglio (2000) reviewed 7 studies that estimated the rebound effect for light-duty vehicles in the United States using the elasticity of vehicle use with respect to fuel CPM to measure it and concluded that the U.S. rebound effect was likely to fall in the range of 10-30 percent.[806]

Sorrell (2007) subsequently reviewed 9 primarily European analyses and found considerably higher values; the studies based on fuel efficiency he reviewed suggested a figure of 40 percent, while the few based on fuel cost per km indicated a range of 5-30 percent. Sorrell et al. (2009) later expanded that earlier survey to include 16 – again mostly European – studies and arrived at similar results, reporting a mean estimate of 44 percent for studies that measured the rebound effect as a response to variation in fuel efficiency but a mean value less than half that (21 percent) for those based on fuel cost per km traveled.[807] For various reasons, those authors speculated that the lower end of the range they identified might be most appropriate.

Table 4-16: Findings from Previous Surveys of the Fuel Economy Rebound Effect

Author(s) and Publication Year	# of Studies Reviewed	Estimates Based on Fuel Economy or Efficiency				Estimates Based on Fuel Cost per Mile or km				Recommended Values	
		N	Mean	Low	High	N	Mean	Low	High	U.S.	Global
Greening et al. (2000)	7	–	–	–	–	13	20%	5%	31%	10-30%	–
Sorrell (2007)	9	4	40%	0%	87%	5	–	5%	30%	–	10-30%

[806] Greening, L.A. et al. 2000. Energy Efficiency and Consumption—the Rebound Effect—A Survey. *Energy Policy*. Vol. (28): pp. 389-401. Available at: https://doi.org/10.1016/S0301-4215(00)00021-5. (Accessed: Feb. 13, 2024).
[807] Sorrell, S. et al. 2009. Empirical Estimates of the Direct Rebound Effect: A Review. *Energy Policy*. Vol. 37: pp. 1356–71. Available at: https://EconPapers.repec.org/RePEc:eee:enepol:v:37:y:2009:i:4:p:1356-1371. (Accessed: Feb. 13, 2024).

Author(s) and Publication Year	# of Studies Reviewed	Estimates Based on Fuel Economy or Efficiency				Estimates Based on Fuel Cost per Mile or km				Recommended Values	
		N	Mean	Low	High	N	Mean	Low	High	U.S.	Global
Sorrell et al. (2009)	16	5	44%	0%	87%	12	21%	6%	32%	–	10-30%
Dimitropoulos et al. (2018)	69	203	27%	-64%	133%	445	20%	-28%	145%	~20%	26-29%

Most recently, a meta-analysis of 74 published studies of the rebound effect conducted by Dimitropoulos et al. (2018) found extremely wide variation in reported values, estimating that the long-run rebound effect averaged 27 percent when measured by the response of vehicle use to variation in fuel efficiency (the authors' preferred measure), and 20 percent when it is measured using variation in fuel cost per unit of distance traveled.[808] The authors concluded that "the magnitude of the rebound effect in road transport can be considered to be, on average, in the area of 20 [percent]," but noted that their most likely long-run estimate was about 32 percent.[809]

A subsequent study by these same authors concluded that the most likely estimate of the long-run rebound effect is in the range of 26-29 percent.[810] Thus, the finding from these surveys that the rebound effect offsets only a relatively modest share of total potential fuel savings has remained surprisingly consistent over time, despite a rapidly expanding universe of empirical evidence drawn from increasingly diverse settings, continuing improvements in the data available to measure it, an expanding range of strategies for identifying the rebound effect and distinguishing it from other factors influencing vehicle use, and advances in the econometric procedures analysts use to estimate its magnitude.

On the basis of the evidence reviewed here, NHTSA has elected to use a rebound effect of 10 percent to analyze the effects of adopting higher CAFE standards and fuel efficiency standards for HDPUVs. It is rarely possible to identify whether estimates of the rebound effect apply specifically to household vehicles, light-duty vehicles, or another category, and different nations classify the large light trucks included in NHTSA's HDPUV category in varying ways, so the agency has assumed the same value for light-duty vehicles and HDPUVs.

NHTSA's assessment of the probability distributions presented here is that the median values of three of the five probability distributions shown in Figure 4-20: Probability Distribution of Rebound Effect Estimates Based on Fuel Economy or Fuel Efficiency and of seven of the eight distributions shown in Figure 4-21 lie in the range of 10-15%, and occasionally even above 15%. In weighing the available evidence, NHTSA considered factors similar to those cited by the EPA in its final rule and found by Dimitropoulos et al. (2018) to account for much of the wide variation among estimates reported in international studies. Specifically, the agency focused particularly on:

- estimates for the U.S. versus those for countries with differing transportation systems, fuel prices, population densities and income levels
- those derived using more recent data or taking into account the potential for the rebound effect to change over time in response to factors such as rising income and increasing fuel economy (for example, Hymel and Small (2015) and Greene (2010))
- estimates based on multiple years of data versus those derived from a single year of survey data (which tend to produce the highest and most variable estimates)
- values that are based on fuel efficiency or fuel CPM rather than the price of gasoline itself
- estimates derived from more reliable data sources such as the U.S. Department of Transportation's historical statistics on aggregate vehicle use or odometer readings for individual vehicles (e.g., Gillingham

[808] Dimitropoulos, A. et al. 2016. The Rebound Effect in Road Transport: A
Meta-Analysis of Empirical Studies. Paris. OECD Environment Working Papers. No. 113; see esat Table 5, at p. 25 (and accompanying discussion).
[809] *Id.* at 28.
[810] Dimitropoulos, A. et al. 2018. The Rebound Effect in Road Transport: A Meta-Analysis of Empirical Studies. *Energy Economics*. Vol. (75): pp. 163–79; see esat Table 4, at 170, Table 5, at 172 (and accompanying discussion), and Appendix B, Table B.V., at 177.

et al. (2015), Knittel and Sandler (2018), Wenzel and Fujita (2018) and West et al. (2015)), rather than owners' self-reported estimates of driving.

When these characteristics are taken into account, the totality of the evidence appears to support using a rebound effect of 10 percent for this current analysis. Because the range of plausible values includes both smaller and larger values, we include sensitivity analyses that use rebound effects of 5 percent and 15 percent. As previously, the agency will continue to review new evidence on the magnitude of the fuel economy rebound effect, update its summaries of that evidence, and adjust the value it employs in regulatory future analysis as appropriate.

4.3.6. VMT Resulting from Simulation

The estimated contribution of each model year cohort to total annual vehicle use depends on the number and types of vehicles initially produced and sold, their annual rates of retirement as they age, the base year mileage accumulation schedules (described in Table 4-12), how future prices compare to their level during the base year, any redistribution of VMT among vehicles of different ages necessary to preserve the non-rebound VMT constraint, and any additional driving attributable to the rebound effect. As discussed in detail above, the estimates of "non-rebound" VMT developed for this analysis reflect only the additional miles associated with normal fleet turnover and changes in fuel prices and exclude all effects of increased fuel economy after 2016. Conversely, rebound miles measure the contribution to VMT of all fuel economy improvements occurring after model year 2016, together with gradual increases in fleetwide fuel economy resulting from continued retirement of older vehicles and their replacement with newer ones.

To calculate total VMT under each regulatory alternative during a future calendar year, including the increase resulting from the fuel economy rebound effect, the CAFE Model first applies the price elasticity of VMT derived from the FHWA forecasting model (-0.085) to the change in fuel CPM resulting from (1) the difference in fuel prices between the current calendar year and the 2016 odometer data base year, and (2) any improvements in fuel economy for vehicles of different ages since the 2016 base year that occurs under the No-Action alternative. It uses the result of that calculation to adjust the average annual VMT for vehicles of each age summarized in the initial base year VMT schedules.

Next, it raises or lowers average annual VMT for vehicles of each age as necessary for total annual VMT (given the number of vehicles of each age remaining in use) to equal the independently forecast value of total VMT for that year (the constraint described previously). Finally, it applies the (user defined) value of the rebound effect and the incremental reduction in fuel CPM resulting from the gains in fuel economy of new vehicles required by each regulatory alternative to calculate the contribution of rebound effect travel to that year's total VMT.

Equation 4-16 presents this calculation:

Equation 4-16: Total Calendar Year VMT with Rebound Miles

$$\text{ReboundVMT}_{CY}=\sum_{A}^{Ages}\sum_{S}^{Styles}\left(\begin{array}{c}\text{VMT}_{A,S}\cdot\left(1+\%\Delta\text{CPM}_{MY,CY}\cdot\varepsilon_{Rbd}\right)\\ +\Delta\text{Miles}_{CY,A,S}\cdot\left(1+\left(\%\Delta\text{CPM}_{MY,CY}\cdot\varepsilon_{Rbd}-\%\Delta\text{NonRbdCPM}_{MY,CY}\cdot\varepsilon_{FHWA}\right)\right)\\ \cdot\text{Population}_{CY,A,S}\end{array}\right)$$

In the equation, $VMT_{A,S}$ is the initial or base year VMT schedule by age and body-style, $\%\Delta CPM$ and $\%\Delta NonReboundCPM$ are as defined in Equation 4-10 and Equation 4-11, and $\Delta Miles_{A,S,CY}$ is the number of miles by which the reallocation described in Equation 4-15 raises or lowers average annual driving for vehicles of each body style and age. This component ($\Delta Miles_{A,S,CY}$) is excluded for HDPUVs. Note that in Equation 4-16, any miles added or deducted in the reallocation step ($\Delta Miles_{CY,A,S}$) are multiplied by only the *difference* between the effects of changes in CPM and non-rebound CPM. This is because $\%\Delta NonRbdCPM$ was used to derive those reallocated miles, so using the full value of ΔCPM to scale those reallocated miles would account for that change twice.

Taking this difference avoids overestimating the total mileage in the presence of the rebound effect. The presence of both the elasticity from the FHWA model that is used to develop the constraining value of non-rebound VMT, ε_{FHWA}, and the user-defined rebound effect, ε_{Rbd}, ensure consistency with the constraint even if the user specifies a value for the rebound that does not equal the elasticity in the FHWA model. The contribution of rebound effect travel will be the difference between Equation 4-16 and Equation 4-15 for each alternative, and to the extent that different regulatory scenarios produce comparable numbers of rebound miles in early calendar years, the impacts associated with those miles will approximately net out across the alternatives in the benefit cost analysis. During later calendar years of the analysis period, however, differences among regulatory alternatives will continue to grow and the contribution of rebound-effect driving to economic and safety impacts will increase, particularly for the most stringent alternatives considered.

5. Simulating Emissions Impacts of Regulatory Alternatives

This final rule includes various fuel-saving technologies, which produce additional co-benefits. These co-benefits include reduced vehicle exhaust emissions during operation as well as reduced upstream emissions during petroleum extraction, transportation, refining, and finally fuel transportation, storage, and distribution. This chapter includes a detailed discussion on the development and evolution of input parameters for criteria pollutants, greenhouse gases, and air toxics emitted.

CAFE Model Files Referenced in this Chapter

Below is a list of CAFE Model Files referenced in this chapter. See Chapter 2.1.9 “Where to Find the Internal NHTSA Files?” for a full list of files referenced in this document and their respective file locations.

- Parameters Input File
- BenMAP Health Incidence Files
- BenMAP EC/OC Health Incidence Files
- CAFE Model Documentation

The rule implements an emissions inventory methodology for estimating impacts. Vehicle emissions inventories are often described as three-legged stools, comprised of activity (i.e., miles traveled, hours operated, or gallons of fuel burned), population (or number of vehicles), and emission factors. An emissions factor is a representative rate that attempts to relate the quantity of a pollutant released to the atmosphere per unit of activity.

In this rulemaking, upstream emission factors are on a fuel volume basis and downstream emission factors are on a distance basis. Simply stated, the rule’s upstream emission inventory is the product of the per-gallon emission factor and the corresponding number of gallons of gasoline or diesel consumed. Similarly, the downstream emission inventory is the product of the per-mile emission factor and the appropriate miles traveled estimate. The only exceptions are that vehicle-based sulfur oxides (SOx) and carbon dioxide (CO_2) also use a per-gallon emission factor in the CAFE Model. The activity levels—both miles traveled and fuel consumption—are generated by the CAFE Model while the emission factors have been incorporated from other federal models. Electric vehicles do not produce combustion-related emissions,[811] however, EV upstream electricity emissions are accounted for in the CAFE Model inputs.

For this rule, downstream and upstream emission factors and subsequent inventories were developed independently from separate data sources. Upstream emission factors are estimated from a lifecycle emissions model developed by the U.S. Department of Energy’s (DOE) Argonne National Laboratory. Downstream emission factors are estimated from the regulatory highway emissions inventory model developed by the U.S. Environmental Protection Agency’s (EPA) National Vehicle and Fuel Emissions Laboratory. Data from the latest EPA and DOE models have been utilized to update the CAFE Model for this rulemaking.

This chapter also details our estimate of how these emissions could adversely affect human health, especially from criteria pollutants known to cause poor air quality and damage human health, particularly when inhaled. Further description of how the health impacts of upstream and downstream criteria pollutant emissions can vary and how these emission damages have been monetized and incorporated into the rule can be found in Chapter 6.2.2 and the Final EIS accompanying this analysis.

5.1. Activity Levels Used to Calculate Emissions Impacts

Emission inventories in this rule vary by several key activity parameters, especially relating to the vehicle’s model year and relative age. Most importantly, the CAFE Model accounts for vehicle sales, turnover, and scrappage as well as travel demands over a vehicle’s lifetime. Like other models, the CAFE Model includes procedures to estimate annual rates at which new vehicles are purchased, driven, and subsequently scrapped. Together, these procedures result in, for each vehicle model in each model year, estimates of the

[811] Battery-electric vehicles (BEVs) do not produce any exhaust emissions while plug-in hybrid electric vehicles (PHEVs) only produce exhaust emissions during use of conventional fuels. Utilization factors typically define how much real-world operation occurs while using electricity versus conventional fuels.

number remaining in service in each calendar year, as well as the annual mileage accumulated (i.e., VMT) at each age. Inventories by model year are derived from the annual mileage and corresponding emission factors.

As discussed in Chapter 2.1, for each vehicle model/configuration in each model year from 2022 to 2050 for upstream estimates and 2060 for downstream estimates, the CAFE Model estimates and records the fuel type (e.g., gasoline, diesel, electricity), fuel economy, and number of units sold in the U.S. The model also makes use of an aggregated representation of vehicles sold in the U.S. during 1983-2022. The model estimates the numbers of each cohort of vehicles remaining in service in each calendar year, and the amount of driving accumulated by each such cohort in each calendar year.

The CAFE Model estimates annual vehicle miles of travel (VMT) for each individual car and light truck model produced in each model year at each age of their lifetimes, which extend for a maximum of 40 years. Since a vehicle's age is equal to the current calendar year minus the model year in which it was originally produced, the age span of each vehicle model's lifetime corresponds to a sequence of 40 calendar years beginning in the calendar year corresponding to the model year it was produced. These estimates reflect the gradual decline in the fraction of each car and light truck model's original model year production volume that is expected to remain in service during each year of its lifetime, as well as the well-documented decline in their typical use as they age. Using this relationship, the CAFE Model calculates fleet-wide VMT for cars and light trucks in service during each calendar year spanned by this analysis.

Based on these estimates, the model also calculates quantities of each type of fuel or energy, including gasoline, diesel, and electricity, consumed in each calendar year. By combining these with estimates of each model's fuel or energy efficiency, the model also estimates the quantity and energy content of each type of fuel consumed by cars and light trucks at each age, or viewed another way, during each calendar year of their lifetimes. As with the accounting of VMT, these estimates of annual fuel or energy consumption for each vehicle model and model year combination are combined to calculate the total volume of each type of fuel or energy consumed during each calendar year, as well as its aggregate energy content.

The procedures the CAFE Model uses to estimate annual VMT for individual car and light truck models produced during each model year over their lifetimes and to combine these into estimates of annual fleet-wide travel during each future calendar year, together with the sources of its estimates of their survival rates and average use at each age, are described in detail in Chapters 4.2 and 4.3. The data and procedures the CAFE Model employs to convert these estimates of VMT to fuel and energy consumption by individual model, and to aggregate the results to calculate total consumption and energy content of each fuel type during future calendar years, are also described in detail in that same subchapter.

The CAFE Model Documentation accompanying this final rule describes these procedures in detail. The quantities of travel and fuel consumption estimated for the cross section of model years and calendar years constitutes a set of "activity levels" based on which the model calculates emissions. The model does so by multiplying activity levels by emission factors. As indicated in the previous subchapter, the resulting estimates of vehicle use (i.e., VMT), fuel consumption, and fuel energy content are combined with emission factors drawn from various sources to estimate emissions of GHGs, criteria air pollutants, and airborne toxic compounds that occur throughout the fuel supply and distribution process, as well as during vehicle operation, storage, and refueling. Emission factors measure the mass of each GHG or criteria pollutant emitted per vehicle mile of travel, gallon of fuel consumed, or unit of fuel energy content. The following subchapter identifies the sources of these emission factors and explains in detail how the CAFE Model applies them to its estimates of vehicle travel, fuel use, and fuel energy consumption to estimate total annual emissions of each GHG, criteria pollutant, and airborne toxic.

5.2. Simulating Upstream Emissions Impacts

The CAFE standards included in this final rule consider both downstream and upstream emissions in the cost-benefit analysis and rulemaking documentation. Early CAFE rulemakings utilized upstream emission factors from the U.S. Department of Energy's previous releases of the Greenhouse Gases, Regulated Emissions, and Energy use in Transportation (GREET) Model.[812] This rule includes data from GREET 2023 and additionally uses a data processing script to manipulate formats, allowing for quicker, easier replication. Rulemaking updates to upstream emissions were made for certain fuel types:

- Gasoline,
- Diesel, and
- Electricity.

This chapter provides the calculation methodology of these updated upstream emission factors (in grams/mmBTU) for the following regulated criteria pollutants as well as greenhouse gases derived from GREET:

- Regulated criteria pollutants
    - carbon monoxide (CO),
    - volatile organic compounds (VOCs),
    - nitrogen oxides (NO_x),
    - sulfur oxides (SO_x), and
    - particulate matter with 2.5-micron (µm) diameters or less ($PM_{2.5}$);
- Greenhouse gases
    - carbon dioxide (CO_2),
    - methane (CH_4), and
    - nitrous oxide (N_2O).

Emission factors for air toxics and PM of 10 µm or less (PM_{10}) were unchanged from previous CAFE rules.

Each analysis year has emission factors of the four upstream emission processes for gasoline and diesel:

- Petroleum Extraction,
- Petroleum Transportation,
- Petroleum Refining, and
- Fuel Transportation, Storage, and Distribution (TS&D).

By contrast, electricity only has a single value per analysis year. In the subchapters below, the specific emission calculations for each upstream process are described. The upstream CAFE Model parameters for this rule include 2022 through 2050 in five-year intervals:

- 2022, 2025, 2030, 2035, 2040, 2045, 2050

5.2.1. Petroleum Extraction

The first step in the process for calculating upstream emissions includes any emissions related to the extraction, recovery, and production of petroleum-based feedstocks, namely conventional crude oil, oil sands, and shale oils. This methodology was initially implemented by Volpe with example guidance from the Department of Energy's Argonne National Laboratory. The Petroleum Extraction calculation began by summing all of the emission factors by extraction subprocess from the GREET 2023 Petroleum tab. For example, the emission factor EF of oil sands surface mining for diluted bitumen (dilbit) production is the sum of each extraction subprocess EF: bitumen extraction and separation, on-site H2 production, co-produced electricity credit, flaring emissions, and bitumen extraction and separation non-combustion emissions.

Each extraction *EF* is then multiplied by the associated loss factors—or process inefficiencies (usually equal to one for no loss or slightly less than one)—and energy share for the following combinations of feedstock and primary extraction process:

[812] Argonne National Laboratory. Energy Systems and Infrastructure Analysis. Greenhouse gases, Regulated Emissions, and Energy Use in Technologies Model (GREET). Last Update: Oct. 11, 2022. Available at: https://greet.es.anl.gov/. (Accessed: Feb. 13, 2024).

- Crude Oil
  - Recovery
- Oil Sands
  - Surface Mining + Dilbit
- Bitumen Extraction and Separation,
  - On-site H2 Production,
  - Co-produced Electricity Credit,
  - Flaring Emissions, and
  - Bitumen Extraction and Separation Non-Combustion Emissions;
- Surface Mining + Synthetic Crude Oil (SCO)
  - Bitumen Extraction and Separation,
  - On-site H2 Production,
  - Co-produced Electricity Credit,
  - Flaring Emissions, and
  - Bitumen Extraction and Separation Non-Combustion Emissions;
- In-Situ Production + Dilbit
  - Bitumen Extraction and Separation,
  - On-site H2 Production,
  - Co-produced Electricity Credit,
  - Flaring Emissions, and
  - Bitumen Extraction and Separation Non-Combustion Emissions;
- In-Situ Production + SCO
  - Bitumen Extraction and Separation,
  - On-site H2 Production,
  - Co-produced Electricity Credit,
  - Flaring Emissions, and
  - Bitumen Extraction and Separation Non-Combustion Emissions;
- Shale Oil (Bakken)
  - Recovery
- Shale Oil (Eagle Ford)
  - Recovery

These seven upstream feedstock/extraction process combinations produce identical estimates for both gasoline and diesel; differences by fuel type only occur during and after the refining process. The extraction calculation includes the two associated loss factors, that are constant across all analysis years and both fuel types, and energy share (rather than the volumetric share) for each combination above:

- Loss Factors
  - Transportation to U.S. Refineries
  - Storage
- Energy Share of Crude Feedstocks to U.S. Refinery

In mathematical terms, the Petroleum Extraction calculation for the emission factor *EF* dependent on the energy share *es* (from the GREET Petroleum tab), fuel type *f* (either gasoline or diesel), analysis year *y*, and pollutant *p* can be expressed as shown in Equation 5-1.

Equation 5-1: Yearly Gasoline Petroleum Extraction Emission Factor

$$EF_{petrol\ extract_{f,\ y,\ p}} = \left(EF_{crude\ oil_{f,y,p}} \cdot loss_{trans} \cdot loss_{storage} \cdot es_{crude\ oil_{y}}\right)$$

$$+\left(EF_{surface\ mining,\ dilbit_{f,y,p}} \cdot loss_{trans} \cdot loss_{storage} \cdot es_{surface\ mining,\ dilbit_y}\right)$$
$$+\left(EF_{surface\ mining,\ SCO_{f,y,p}} \cdot loss_{trans} \cdot loss_{storage} \cdot es_{surface\ mining,\ SCO_y}\right)$$
$$+\left(EF_{in\text{-}situ,\ dilbit_{f,\ y,p}} \cdot loss_{trans} \cdot loss_{storage} \cdot es_{in\text{-}situ,\ dilbit_y}\right)$$
$$+\left(EF_{in\text{-}situ,\ SCO_{f,y,p}} \cdot loss_{trans} \cdot loss_{storage} \cdot es_{in\text{-}situ,SCO_y}\right)$$
$$+\left(EF_{Bakken\ shale_{f,y,p}} \cdot loss_{trans} \cdot loss_{storage} \cdot es_{Bakken\ shale_y}\right)$$
$$+\left(EF_{Eagle\ Ford\ shale_{f,y,p}} \cdot loss_{trans} \cdot loss_{storage} \cdot es_{Eagle\ Ford\ shale_y}\right)$$

For every year in the series of analysis years $y \in Y$ (note that the year evaluated must be changed in the GREET Inputs tab) and every pollutant in the full set of pollutants $p \in P$ mentioned above, the final gasoline Petroleum Extraction *EF* is multiplied by the percent non-ethanol remainder of the standard E10 blend currently distributed at fuel pumps across the U.S. (also found in the GREET Petroleum tab), simply 1 – pure ethanol energy content $(EC_{EtOH}\ \%)$ while the final diesel *EF* is assumed to have no ethanol content, such that:

Equation 5-2: Total Gasoline Petroleum Extraction Emission Factor

$$EF'_{petrol\ extract_{gas,\ y \in Y,\ p \in P}} = EF_{petrol\ extract_{gas,\ y \in Y,\ p \in P}} \cdot (1 - EC_{EtOH}\ \%), \text{ and}$$

$$EF'_{petrol\ extract_{diesel,\ y \in Y,\ p \in P}} = EF_{petrol\ extract_{diesel,\ y \in Y,\ p \in P}}.$$

There are a few notable pollutant exceptions that have been originally separated out in GREET by their sources and were later combined in the extraction calculation:

$$Total\ VOC = VOC + VOC\ from\ bulk\ terminal, \text{ and}$$

$$Total\ CH_4 = CH_4{:}combustion + CH_4{:}non\text{-}combustion.$$

Many extraction processes do not include *VOC from bulk terminal* and *CH_4: non-combustion* but are added to primary VOC and CH_4 estimates respectively for crude oil and shale oil recovery. The Petroleum Transportation and Fuel TS&D processes also consider combined VOC and CH_4 emission factors.

5.2.2. Petroleum Transportation

The Petroleum Transportation process is quite similar to the Petroleum Extraction process described above, but instead only includes the transport processes of crude feedstocks sent for domestic refining:

- Crude Oil
  - Transportation to U.S. Refineries
- Oil Sands
  - Surface Mining + Dilbit: Transportation to U.S. Refineries,
  - Surface Mining + SCO: Transportation to U.S. Refineries,
  - In-Situ Production + Dilbit: Transportation to U.S. Refineries, and
  - In-Situ Production + SCO: Transportation to U.S. Refineries;
- Shale Oil (Bakken)
  - Transportation to U.S. Refineries
- Shale Oil (Eagle Ford)
  - Transportation to U.S. Refineries

While the Petroleum Transportation calculation does still use energy share *es* by crude feedstock, it omits the loss factors. As with Petroleum Extraction, the Petroleum Transportation emission factor *EF*, shown in

Equation 5-3, is aggregated by feedstock/process combinations also located in the GREET 2023 Petroleum tab.

Equation 5-3: Yearly Gasoline Petroleum Transportation Emission Factor

$$\begin{aligned} & EF_{petrol\ transport_{f,\ y,\ p}} \\ & = \left(EF_{crude\ oil_{f,y,p}} \cdot es_{crude\ oil_{y}}\right) \\ & + \left(EF_{surf\ mining,\ dilbit_{f,y,p}} \cdot es_{surf\ mining,\ dilbit_{y}}\right) \\ & + \left(EF_{surf\ mining,\ SCO_{f,y,p}} \cdot es_{surf\ mining,\ SCO_{y}}\right) \\ & + \left(EF_{in\text{-}situ,\ dilbit_{f,\ y,p}} \cdot es_{in\text{-}situ,\ dilbit_{y}}\right) \\ & + \left(EF_{in\text{-}situ,\ SCO_{f,y,p}} \cdot es_{in\text{-}situ,SCO_{y}}\right) \\ & + \left(EF_{Bakken\ shale_{f,y,p}} \cdot es_{Bakken\ shale_{y}}\right) \\ & + \left(EF_{Eagle\ Ford\ shale_{f,y,p}} \cdot es_{Eagle\ Ford\ shale_{y}}\right) \end{aligned}$$

As in the extraction process calculation, the crude feedstock transportation *EFs* are generated for each fuel type *f*, year in the series of analysis years $y \in Y$, and each pollutant is the full set of pollutants $p \in P$. The final Petroleum Transportation *EF* for gasoline is multiplied by the national default non-ethanol remainder $(1\text{-}EC_{EtOH}\ \%)$, whereas the final transport *EF* for diesel will not contain any ethanol, shown in Equation 5-4.

Equation 5-4: Total Gasoline Petroleum Transportation Emission Factor

$$EF'_{petrol\ transport_{gas,\ y\in Y,\ p\in P}} = EF_{petrol\ transport_{gas,\ y\in Y,\ p\in P}} \cdot (1\text{-}EC_{EtOH}\ \%), \text{ and}$$

$$EF'_{petrol\ transport_{diesel,\ y\in Y,\ p\in P}} = EF_{petrol\ transport_{diesel,\ y\in Y,\ p\in P}}.$$

Lastly, the total VOC for Petroleum Transportation is the sum of the primary VOC and the VOC from bulk terminal as shown above for Petroleum Extraction while the total CH_4 is comprised of the combustion component alone.

5.2.3. Petroleum Refining

Unlike the Petroleum Extraction and Petroleum Transportation calculations, the Petroleum Refining calculation is based on the aggregation of fuel blendstock processes rather than the crude feedstock processes. In GREET 2023, the refining processes are found in the finished gasoline and low-sulfur diesel subchapters of the Petroleum tab, as listed below:

- Gasoline
- Gasoline Blendstock Refining: Feed Inputs
- Gasoline Blendstock Refining: Intermediate Product Combustion
- Gasoline Blendstock Refining: Non-Combustion Emissions
- Low-Sulfur Diesel
- LS Diesel Refining: Feed Inputs
- LS Diesel Refining: Intermediate Product Combustion
- LS Diesel Refining: Non-Combustion Emissions

Since the distribution of crude feedstocks is not considered directly in the refining process, the finished fuel transportation loss adjustment (Gasoline Blendstock Transportation and LS Diesel Transportation Distribution respectively) is factored into the refining emission factor *EF* calculation while the energy share *es* is not. This leads to Equation 5-5 for the Petroleum Refining process.

Equation 5-5: Yearly Gasoline Petroleum Refinery Emission Factor

$$EF_{petrol\ refine_{f,\ y,\ p}} = \left(EF_{feed\ inputs_{f,y,p}} + EF_{intermediate\ combust_{f,y,p}} + EF_{non\text{-}combust_{f,y,p}}\right) \cdot loss_{blend\ transportation_y}$$

In a similar fashion to the extraction and transportation processes of crude feedstocks, the final Petroleum Refining *EF* for gasoline applies the non-ethanol energy content adjustment $(1\text{-}EC_{EtOH}\ \%)$ for E10. The final Petroleum Refining *EF* for diesel does not apply any such non-ethanol adjustment because the fuel is purely based on petroleum. The final refining *EFs* can be written as shown in Equation 5-6.

Equation 5-6: Total Gasoline Petroleum Refinery Emission Factor

$$EF'_{petrol\ refine_{gas,\ y\epsilon Y,\ p\epsilon P}} = EF_{petrol\ refine_{gas,\ y\epsilon Y,\ p\epsilon P}} \cdot (1\text{-}EC_{EtOH}\ \%), \text{ and}$$

$$EF'_{petrol\ refine_{diesel,\ y\epsilon Y,\ p\epsilon P}} = EF_{petrol\ refine_{diesel,\ y\epsilon Y,\ p\epsilon P}}.$$

In the refining calculations, there are no exceptions for VOC or CH_4. Both primary VOC and CH_4 combustion account for the total VOC and total CH_4 respectively.

5.2.4. Fuel TS&D

The final upstream process after refining is the TS&D of the finished fuel product. For gasoline, the blendstock transportation and distribution subprocesses were previously combined in a single GREET value on the Petroleum tab, but now these emission factors are reported separately to avoid double-counting of pre-blended E0 transportation in the Fuel TS&D process. This issue does not exist for low-sulfur diesel, which does not require blending like E10. The Fuel TS&D subprocesses for gasoline and diesel in GREET 2023 are summarized:

- Gasoline
    - Gasoline Blendstock Transportation
    - Gasoline Blendstock Distribution
    - Gasoline Distribution
    - Gasoline Storage
- Low-Sulfur Diesel
    - LS Diesel Transportation Distribution
    - LS Diesel Storage

In the default settings, GREET does not report any emissions associated with fuel storage. Given that all storage *EFs* are zero, the initial Fuel TS&D calculation with GREET 2023 is just the reported *EFs* for E0 blendstock transportation and distribution.

Equation 5-7: Yearly E0 Blendstock Transportation and Distribution Emission Factor

$$EF_{fuel\ TS\&D_{f,\ y,\ p}} = EF_{E0\ blend\ trans_{f,y,p}} + EF_{E0\ blend\ dist_{f,y,p}}$$

The final Fuel TS&D *EF* for gasoline accounts for emissions before and after E10 blending. This final gasoline *EF* utilizes the percent energy content of the non-ethanol remainder—the same as earlier petroleum processes. It also incorporates ethanol energy content with upstream ethanol for gasoline blending *EFs* on the GREET EtOH tab, where the total ethanol *EF* is the sum of its fuel and feedstock subprocesses.

Equation 5-8: Fuel Transportation and Distribution Emission Factor with E10 Blending

$$EF_{EtOH \rightarrow gas\ blend_{y,p}} = EF_{EtOH \rightarrow gas\ blend,\ fuel_{y,p}} + EF_{EtOH \rightarrow gas\ blend,\ feedstock_{y,p}}$$

The final Fuel TS&D *EFs* for gasoline and for diesel can be broken into three terms, E0 distribution, ethanol TS&D, and E10 distribution, such that in GREET 2023:

Equation 5-9: Total Fuel Transportation and Distribution Emission Factor

$$EF'_{fuel\ TS\&D_{gas,\ y\in Y,\ p\in P}} = \left(EF_{E0\ blend\ dist_{gas,\ y\in Y,\ p\in P}} \cdot (1\text{-}EC_{EtOH}\ \%)\right) + \left(EF_{EtOH\ \rightarrow gas\ blend_{y\in Y,\ p\in P}} \cdot EC_{EtOH}\ \%\right) + EF_{E10\ dist_{gas,\ y\in Y,\ p\in P}}, \text{ and}$$

$$EF'_{fuel\ TS\&D_{diesel,\ y\in Y,\ p\in P}} = EF_{TS\&D_{diesel,\ y\in Y,\ p\in P}}$$

These Fuel TS&D equations have omitted the non-existent storage terms for simplicity.

Equation 5-10: E0 Blend Distribution Emission Factor

$$EF_{E0\ blend\ dist_{gas,\ y\in Y,\ p\in P}} = EF_{E0\ blend\ T\&D_{gas,\ y\in Y,\ p\in P}} - EF_{E0\ blend\ trans_{gas,\ y\in Y,\ p\in P}}$$

Total CH4 for Fuel TS&D is based solely on the CH_4: combustion component and total VOC is the sum of the primary VOC and other components from the T&D process.

Equation 5-11: Total Volatile Organic Compounds from the Transportation and Distribution Process

$$Total\ VOC = VOC + VOC\ from\ bulk\ terminal + VOC\ from\ ref.\ \ station.$$

However, for the gasoline TS&D calculation in GREET 2023, the primary VOC comes from the blendstock distribution while the other VOC components come from the blendstock transportation.

5.2.5. Aggregated Gasoline and Diesel Emission Factors

The upstream gasoline and diesel *EFs* for this analysis continue to be aggregated using the same method as the 2022 final rule and earlier rulemakings. While the particular gasoline and diesel *EFs* vary by analysis year and pollutant, the aggregation of the four upstream processes—Petroleum Extraction, Petroleum Transportation, Petroleum Refining, and Fuel TS&D—follows the same calculation for both fuel types. The CAFE Model aggregation method differs from the GREET method and considers the following two upstream criteria emission adjustments for CAFE:

- Share of Fuel Savings Leading to Reduced Domestic Fuel Refining, and
- Share of Reduced Domestic Refining from Domestic Crude.

In this case, for criteria emissions, the final aggregation applies a fuel savings adjustment to the Petroleum Refining process and a combined fuel savings and reduced domestic refining adjustment to the pair of Petroleum Extraction and Petroleum Transportation processes for each fuel type in the gasoline-diesel pair $f \in F$, each year in the series of analysis years $y \in Y$, and each pollutant in the full set of pollutants $p \in P$.[813]

Equation 5-12: Aggregated Fuel Emissions Factor

$$EF''_{agg\ y\in Y,\ p\in P} = EF'_{fuel\ TS\&D_{f\in F,y\in Y,\ p\in P}} + \left(EF'_{petrol\ refine_{f\in F,y\in Y,\ p\in P}} \cdot share_{fuel\ savings}\right) + \left(\left(EF'_{petrol\ extract_{f\in F,y\in Y,\ p\in P}} + EF'_{petrol\ transport_{f\in F,y\in Y,\ p\in P}}\right) \cdot share_{fuel\ savings} \cdot share_{reduced\ refine}\right)$$

For GHGs the two share adjustments are not applied since greenhouse gas damages are global in nature. For consistency, these aggregated gasoline and diesel *EF* calculations occur in the CAFE Model rather than

813 See Chapter 6.2.4.3 for further discussion about NHTSA's import assumptions.

the processing script or elsewhere. Note that the upstream adjustments in the CAFE Model are constant across fuel types, analysis years, and are constant within each group of pollutants.

5.2.6. Electricity Emission Factors

Electricity follows an analogous production pathway to petroleum fuels. Most electricity feedstocks are extracted and then transported for refining and then for electricity generation, with the exception of renewable resources ("renewables"), such as solar and wind. Renewables do not need refining and are utilized directly in generation at the source location. Once electricity has been generated, transmission and distribution infrastructure exist to move the electricity to its end use, including to charging stations for transportation applications. For this final rule, the electricity *EF* simply sums the feedstock and fuel subprocesses for every unique analysis year and pollutant.

Equation 5-13: Electricity Transportation Emissions Factor

$$EF_{electric,\ transport\ use_{y\epsilon Y,p\epsilon P}} = EF_{electric,\ transport\ use_{feedstock,y\epsilon Y,p\epsilon P}} + EF_{electric,\ transport\ use_{fuel,y\epsilon Y,p\epsilon P}}$$

Unlike for the upstream gasoline and diesel *EFs*, the CAFE Model utilizes the single upstream electricity *EF* for transportation use highlighted above and does not differentiate by process. Electricity *EFs* were also developed using GREET 2023, which incorporates a national mix of electricity generation, often simply called the grid mix, historically from the Annual Energy Outlook published earlier in the same year.

However, consistent with feedback and additional consultation with the US Department of Energy, the analysis supporting this final rule uses a grid mix from the Electrification Futures Study (EFS),[814] specifically the 2022 Standard Scenarios forecast (mid-case, nascent tech, current policies),[815] developed by the National Renewable Energy Laboratory (NREL). This grid mix forecast was mapped into GREET 2023 to develop the CAFE Model's electricity emission factors. Further discussion is included in the preamble Section III.F and a more detailed assessment of various candidate grid mixes and how we map alternative grid mix forecasts into GREET 2023 is documented in an accompanying docket memo.[816]

5.3. Simulating Downstream Emissions Impacts

Downstream emission factors are generated using the latest regulatory model for on-road emission inventories from the U.S. Environmental Protection Agency, the Motor Vehicle Emission Simulator (MOVES4). This subchapter has two primary components of discussion: 1) preparing model runs to estimate vehicle-based emission inventories and vehicle activity, referred to below as pre-processing, and 2) calculating vehicle-based emission factors on a per-mile basis, referred to below as post-processing. In addition, this subchapter discusses the separate process for generating vehicle-based CO_2 emissions levels in the CAFE Model.

5.3.1. Pre-Processing of MOVES Data

For this rulemaking, the CAFE Model's vehicle-based input parameters for criteria pollutants, non-CO_2 greenhouse gases (excluding HFCs), and mobile-source air toxics have been updated with the latest available emission factors. The most recent version of the Motor Vehicle Emission Simulator (MOVES4), first released in August 2023, is a state-of-the-science, mobile-source emissions inventory model for regulatory applications.[817] New MOVES4 vehicle-based emission factors have been incorporated into the CAFE parameters, and these updates supersede previous MOVES downstream data.

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[814] National Renewable Energy Laboratory. 2022. Electrification Futures Study. Scenario Viewer/Data Downloader, 2022 Standard Scenarios.Available at: https://scenarioviewer.nrel.gov/?project=fc00a185-f280-47d5-a610-2f892c296e51&layout=Default. (Accessed: Jan. 1 2024).
[815] For a list of policies included in the forecast, please refer to Regional Energy Deployment System (ReEDS) Model Documentation: Version 2020, available at https://www.nrel.gov/docs/fy21osti/78195.pdf.
[816] See NHTSA's Electricity Grid Forecast Docket Memo.
[817] EPA. Latest Version of Motor Vehicle Emission Simulator (MOVES). MOVES4: Latest Version of Motor Vehicle Emission Simulator. Last revised: Jan. 18, 2024. Available at: https://www.epa.gov/moves/latest-version-motor-vehicle-emission-simulator-moves. (Accessed: Feb. 13, 2024).

5.3.1.1. Overview of MOVES Modeling

For this rulemaking, all the gasoline and diesel vehicle-based emission factors have been updated across all model years, which accounts for all prior CAFE and vehicle GHG standards.

Detailed MOVES4 run specifications have been listed in Table 5-1. Downstream parameters in the CAFE Model have otherwise maintained their format and extend to model year 2060. The most relevant details from these downstream parameters have been summarized as follows:

- MOVES Release: 4.0.0 (August 2023)
- MOVES Default Database: 20230615
- Fuel Types
  - gasoline
  - diesel
- Vehicle Classes
  - light-duty vehicles (MOVES regulatory class 21)
  - light-duty trucks, Classes 1 and 2a (MOVES regulatory class 30)
  - light-duty trucks, Classes 2b and 3 (MOVES regulatory class 41)
- Model Years[818]: 1983 – 2060
  - Vehicle Ages: 0 – 39 years old
- Criteria Pollutants and Precursors
  - carbon monoxide (CO)
  - volatile organic compounds (VOCs)
  - nitrogen oxides (NO_x)
  - particulate matter with 2.5-micron (µm) diameters or less ($PM_{2.5}$)
  - diesel particulate matter with 10-micron (µm) diameters or less (PM_{10})
- Greenhouse gases
  - methane (CH_4)
  - nitrous oxide (N_2O)
- Air Toxics
  - acetaldehyde
  - acrolein
  - benzene
  - butadiene
  - formaldehyde
  -

Table 5-1: National-Scale Run Specifications

Categories	Variable	Input
Description	-----	<blank>
Scale	Model	Onroad
	Domain/Scale	National
	Calculation Type	Inventory
Time Spans	Time Aggregation Level[819]	Year

[818] Note that unused tailpipe data from model year 1975 to 1982 was removed, MOVES emission factors now begin in model year 1983 as compared to the NPRM.
[819] MOVES runs were performed hourly in order to include evaporative processes, but emission factors were aggregated and reported on an annual basis.

	Years	1990, 1999, 2000, 2001… 2058, 2059, 2060 [each year was run separately]
	Months	All Selected
	Days	All Selected
	Hours	All Selected
Geographic Bounds	-----	Nation
Vehicles/ Equipment	On-Road Vehicle Equipment	Passenger Cars, Passenger Trucks, Light Commercial Trucks (Gasoline, Diesel, Electricity, E85) School Buses (Gasoline, Diesel, Electricity) Short-Haul Single Unit Trucks, Long-Haul Single Unit Trucks, Motor Homes, Refuse Trucks (Gasoline, Diesel, Electricity)
Road Type	Road Type	All Road Types
Pollutants and Processes	Total Gaseous Hydrocarbons	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust, Evap Permeation, Evap Fuel Vapor Venting, Evap Fuel Leaks, Refueling Displacement Vapor Loss, Refueling Spillage Loss
	Non-methane Hydrocarbons	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust, Evap Permeation, Evap Fuel Vapor Venting, Evap Fuel Leaks, Refueling Displacement Vapor Loss, Refueling Spillage Loss
	Volatile Organic Compounds	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust, Evap Permeation, Evap Fuel Vapor Venting, Evap Fuel Leaks, Refueling Displacement Vapor Loss, Refueling Spillage Loss
	Methane (CH_4)	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Carbon Monoxide (CO)	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Oxides of Nitrogen (NO_x)	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Nitrous Oxide (N_2O)	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Primary Exhaust $PM_{2.5}$ – Total	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Primary Exhaust $PM_{2.5}$ – Species	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Primary $PM_{2.5}$ – Brakewear Particulate	Brakewear
	Primary $PM_{2.5}$ – Tirewear Particulate	Tirewear
	Primary Exhaust PM_{10} – Total	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Primary Exhaust PM_{10} – Species	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust

	Primary PM_{10} – Brakewear Particulate	Brakewear
	Primary PM_{10} – Tirewear Particulate	Tirewear
	Sulfur Dioxide (SO_2)	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Carbon Dioxide Equivalent (CO_2e)	Running Exhaust, Start Exhaust
	Total Energy Consumption (TEC)	Running Exhaust, Start Exhaust
	Benzene	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust, Evap Permeation, Evap Fuel Vapor Venting, Evap Fuel Leaks, Refueling Displacement Vapor Loss, Refueling Spillage Loss
	1,3-Butadiene	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Formaldehyde	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Acetaldehyde	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Acrolein	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
Manage Input Data Series	-----	<blank>
Strategies	Rate of Progress	<blank>
General Output	Units	Mass: kilograms, Energy: million BTU, Distance: miles
	Activity	Distance Traveled, Population
Output Emissions Detail	Always	Year, Nation
	On Road/Off Road	Road Type, Source Use Type, Regulatory Class
	For All Vehicle/Equipment Combinations	Model Year, Fuel Type, Emission Process
Advanced Performance Features	-----	<blank>

5.3.1.2. Implementation of MOVES Runs

To begin, a MOVES4 run specification (runspec) for calendar year 2022 was built as a template and then replicated for 1990 and for every year from 1999 to 2060, creating a total of 63 runs. The 2022 template run uses the national-scale specifications denoted in Table 5-1. In addition, the MOVES4 default database accounts for prior CAFE and GHG standards. Beyond designating one year per run, all runs were executed with the same runspecs and modified default database.

Post-processing the MOVES4 data into an appropriate format for the CAFE Model is described below. This post-processing discussion details how the downstream emission factors were calculated from the MOVES4 output databases and then translated for use in the Parameters Input File.

5.3.2. Post-Processing of MOVES Data

The Motor Vehicle Emission Simulator (MOVES4) data were post-processed into input parameters for the CAFE Model using a script for automation. Downstream emission parameters for this rulemaking were updated for gasoline and diesel light-duty vehicles and trucks, including the criteria pollutants, greenhouse gases, and air toxics across model years 1983 to 2060, as mentioned in the run specifications in the MOVES pre-processing discussion above.

5.3.2.1. Overview of Downstream Emissions Data Development from MOVES

As noted earlier, each MOVES4 run created an output database for a single evaluation year, meaning there were 63 total runs and subsequent output databases. Output databases contain a number of tables with model emissions inventories and vehicle activities, such as VMT. The next subchapter describes the specific steps taken to alter the output database from MOVES4.

5.3.2.2. Description of MOVES Output Tables

The MOVES output database contains many tables; however, the post-processing script pulls from only two of these tables:

- movesoutput
- movesactivityoutput

Each table contains many columns, including calendar year, vehicle model year, regulatory class based on vehicle weight and build, fuel type, specific pollutant, and emission inventory, and the vehicle activity. The following columns from each table were used in the post-processing script:

- movesoutput: *yearID, modelYearID, regClassID, fuelTypeID, pollutantID, emissionQuant*
- movesactivityoutput: *yearID, modelYearID, regClassID, fuelTypeID, activity*

5.3.2.3. Connecting to and Querying the MOVES Database

After establishing a MariaDB connection, the code queries the database and returns a dataframe with the following columns:

- yearID, modelYearID, age, regClassID, fuelTypeID, pollutantID, VMT, emissionRate

The age, VMT, and emissionRate columns are calculated from the other columns, which are generated in the default outputs. Age is simply calculated by subtracting the modelYearID from the yearID, while the VMT is taken as the sum of the distance traveled activity and then grouped by yearID, modelYearID, pollutantID, and regClassID for gasoline and diesel separately. Lastly, emissionRate was calculated as the aggregated emissions inventories divided by the aggregated vehicle miles traveled at a corresponding level of resolution.

5.3.2.4. MOVES Data Manipulation

After querying and calculating the columns in the correct units, the next step is simply arranging the data into the appropriate format and copying them to the appropriate Parameters Input File. To do so, we first separate the data into two dataframes by fuel type. We then sort the data by ascending model year, meaning the data begins with calendar year 1990. Within the model year, the data are again sorted by descending age, ascending pollutant, and ascending regulatory class. The resulting dataframe has the structure shown in Table 5-2.

Table 5-2: Example of General MOVES Output

Model Year	Age	Pollutant	Regulatory Class
1983	0		
1983	1		
1983	2		
1983	3		
1983	4		
…	…	…	…
2060	35		
2060	36		
2060	37		
2060	38		
2060	39		

Next, the script pivots this dataframe such that the pollutant and regulatory class values become column headers in the format shown in Table 5-3.

Table 5-3: Example of MOVES Output Prepared in CAFE Parameters Format

	Pollutant	**2**	**2**	**2**	**3**	**3**	**3**	**…**
Model Year	Regulatory Class Age	20	30	41	20	30	41	…
1983	0							
1983	1							
1983	2							
1983	3							
1983	4							
….	…	…	…	…	…	…	…	…
2060	35							
2060	36							
2060	37							
2060	38							
2060	39							

The MOVES4 output does not cover all the model years and ages required by the CAFE Model. MOVES only generates emissions data for vehicles made in the last 30 model years for each calendar year being run. This means emissions data for some calendar year and vehicle age combinations are missing. To remedy this, the script takes the last vehicle age that has emissions data and forward fills those data for the following vehicle ages.

5.3.2.5. Validation Testing of MOVES Updates

To ensure the Parameters Input File was modified correctly, we conducted quality assurance tests, which included some spot-checking of previous emission parameters.

5.3.3. Simulating Downstream CO_2 and SO_x Emissions

Much like the impacts from criteria pollutant emissions, the CAFE input parameters for greenhouse gases are generally taken from other models. As discussed at length above, upstream GHG emission factors come from GREET 2023 and downstream non-CO_2 GHG emission factors (excluding HFCs) come from MOVES4. This subchapter briefly describes the methodology for the development and use of the vehicle-based CO_2 and SO_x emission factors.

5.3.3.1. CO_2 Emissions

For vehicle-based CO_2 emissions, these factors are defined based on the fraction of each fuel type's mass that represents carbon (the carbon content) along with the mass density per unit of the specific type of fuel. To obtain the emission factors associated with each fuel, the carbon content is then multiplied by the mass density of a particular fuel as well as by the ratio of the molecular weight of carbon dioxide to that of elemental carbon (EC). This ratio, a constant value of 44/12, measures the mass of carbon dioxide that is produced by complete combustion of mass of carbon contained in each unit of fuel. The resulting value defines the emission factor attributed to CO_2 as the number of grams of CO_2 emitted during vehicle operation from each type of fuel. This calculation is repeated for gasoline, E85, diesel, and compressed natural gas (CNG) fuel types. In the case of CNG, the mass density and the calculated CO_2 emission factor are denoted as grams per standard cubic feet (scf), while for the remainder of fuels, these are defined as grams per gallon of the given fuel source. As with other pollutants, it is assumed that battery-electricity vehicles will not produce any vehicle-based CO_2 emissions.

5.3.3.2. SO_x Emissions

Sulfur dioxide and other oxides (SO_x) are some of the most harmful criteria pollutants to human health but have been dwindling recently due to the mandated adoption of low-sulfur fuels. With EPA's ultra-low sulfur diesel and Tier 3 gasoline regulations, vehicle-based SO_x emissions from highway vehicles have dropped dramatically.[820,821] As such, there is a strong correlation between the fuel sulfur content and the SO_x emitted, so the CAFE Model utilizes SO_x emission factors based on the energy content (in million British Thermal Units or mmBTU) of the fuel consumed instead of mileage.

For the current rule, SO_x has been estimated directly from EPA's MOVES4 release. Note that MOVES estimates only SO_2 but because SO_2 constitutes 95% of SO_x in combustion or more and the CAFE Model's upstream emissions are reported as SO_x, all sulfur oxide emissions are represented as SO_x.[822,823] Since MOVES predicts that SO_x emission factors (in grams per mmBBTU) will be unchanged after 2022, this analysis assumes constant SO_x rates by fuel type, as summarized in Figure 5-1.

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[820] DieselNet: Fuel Regulations. Diesel Fuel, Sulfur Content. Last revised: Dec. 2009. Available at: https://dieselnet.com/standards/us/fuel.php. (Accessed: May 31, 2023).
[821] EPA. 2023 Gasoline Standards: Gasoline Sulfur. Last revised: Feb. 10, 2023. Available at: https://www.epa.gov/gasoline-standards/gasoline-sulfur. (Accessed: Feb. 13, 2024).
[822] Trijonis, J. 1975. The Relationship of Sulfur Oxide Emissions to Sulfur Dioxide and Sulfate Air Quality. *Air Quality and Stationary Source Emission Control*. Chpt. 6: p. 233. Available at: https://nap.nationalacademies.org/read/10840/chapter/8. (Accessed: Feb. 13, 2024).
[823] The International Council on Combustion Engines. 2008. Guide to Diesel Exhaust Emissions Control of NOx, SOx, Particulates, Smoke, and CO_2: Seagoing Ships and Large Stationary Diesel Power Plants. p. 12. Available at: https://www.cimac.com/cms/upload/Publication_Press/Recommendations/Recommendation_28.pdf. (Accessed: Feb. 13, 2024).

Figure 5-1: Trends in SO_x Emission Factors Over Time by Fuel Type From MOVES4

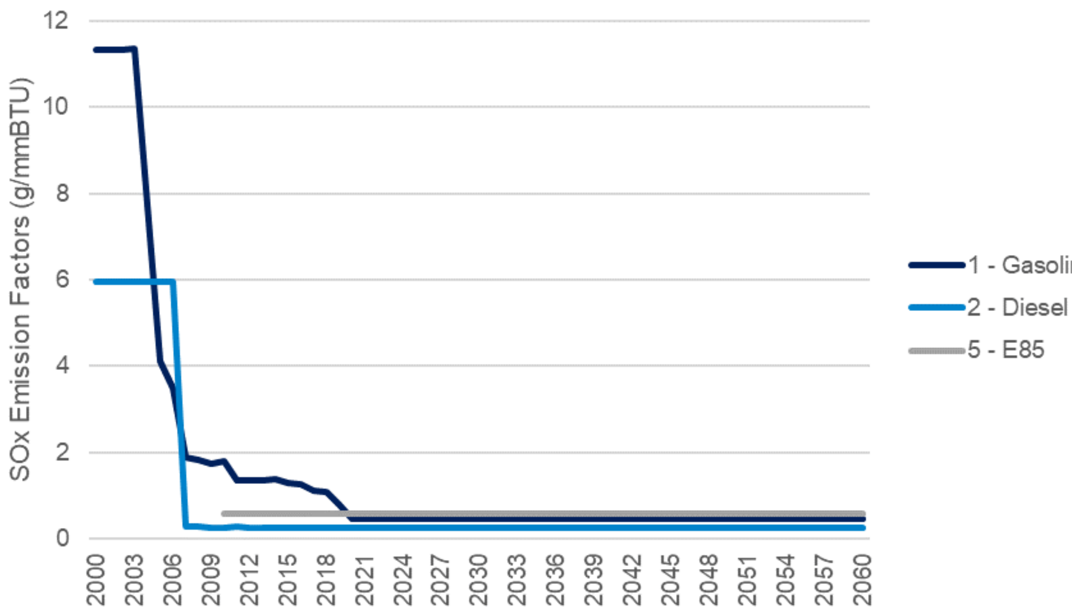


Figure 5-1 highlights how swiftly the fuel sulfur limits impacted mobile-source SO_x emissions. Nonetheless, MOVES predicts stable SO_x emissions for gasoline, diesel, and E85—regardless of regulatory class—after 2022.

5.3.3.3. Summary of CAFE Fuel Properties

Since electricity and hydrogen fuel types do not cause CO_2 or SO_x emissions to be emitted during vehicle operation, the carbon content and the CO_2 emission factors for these two fuel types are assumed to be zero. Any emissions associated with electricity or hydrogen would be during upstream fuel production. For the other fuel types, the table below summarizes the mass density, carbon content, CO_2, and SO_x emission factors.

Table 5-4: CO_2 and SO_x Emission Factors by Fuel Type

Fuel Type	Mass Density (grams/unit)	Carbon Content (% by weight)	CO_2 Emission Factor (grams/unit)	SOx Emissions (grams/MMBTU)
Gasoline (gallons)	2,823	85.9%	8,887	0.364
Ethanol-85 (gallons)	2,963	57.3%	6,226	0.578
Low Sulfur Diesel (gallons)	3,206	86.6%	10,180	0.262
CNG (scf)	19.09	76%	53.20	0.000

The CAFE Model calculates CO_2 vehicle-based emissions associated with vehicle operation of the surviving on-road fleet by multiplying the number of gallons (or scf for CNG) of a specific fuel consumed by the CO_2 emissions factor for the associated fuel type. More specifically, the number of gallons or scf of a particular fuel is multiplied by the carbon content and the mass density per unit of that fuel type, and then the ratio of carbon dioxide emissions generated per unit of carbon consumed during the combustion process is applied.[824]

[824] Chapter 3, Section 4 of the CAFE Model Documentation provides additional description for calculation of CO_2 vehicle-based emissions with the model.

5.3.3.4. Emissions from Brake and Tire Wear

With stringent light-duty vehicle standards already in place for PM from vehicle exhaust, particles from brake and tire wear (BTW) are becoming an increasingly important component of PM emission inventories. Previous CAFE rulemakings have not modeled the indirect impacts to BTW emissions due to changes in fuel economy and vehicle miles traveled. This rule considers PM of diameters less than 2.5 microns ($PM_{2.5}$) from the vehicle's exhaust, brakes, and tires.

All regulatory classes—including passenger cars, light trucks, and heavy-duty pickup trucks and vans (delineated in the CAFE Model Parameters Input File BTW_Emissions tab as "LDT2b/3")—now have separate emission factors for brake wear and for tire wear. Like the CAFE Model powertrain emissions parameters, BTW estimates are modeled using EPA's latest version of the Motor Vehicle Emission Simulator (MOVES4), specifically MOVES4.0.0 released in August 2023. Due to limited BTW measurements, MOVES does not vary BTW factors by model year or fuel type. Instead MOVES brake wear is dependent on its regulatory class based on vehicle weight as well as a reduced set of operating modes based on instantaneous vehicle specific power (VSP) and speed. On the other hand, tire wear is dependent on the weight-based MOVES regulatory classes and operating modes according to speed bin.[825]

There is some evidence that average vehicle weight will differ by fuel type, particularly electric vehicles with extended-range battery packs, which are often heavier than a comparable gasoline- or diesel-powered vehicle.[826] Regenerative braking is likely to extend the useful life of disc brakes and pads and reduce their associated wear, but any additional mass may ultimately increase BTW emissions.[827] However, further BTW data collection from field studies is needed to validate these hypotheses.

For the time being, the CAFE Model's BTW inputs are differentiated by fuel type but have identical values for gasoline, diesel, and electricity. Unlike the CAFE Model's powertrain-associated emission factors, the BTW estimates were averaged over all model years and ages in grams per mile, as summarized in Table 5-5.

Table 5-5: Summary of Brake and Tire Wear Emission Factors by Regulatory Class and Fuel Type

Fuel Type	$PM_{2.5}$ Brake Wear (g/mi)			$PM_{2.5}$ Tire Wear (g/mi)		
	LDV	LDT1/2a	LDT2b/3	LDV	LDT1/2a	LDT2b/3
Gasoline	0.0028	0.0029	0.0031	0.0013	0.0013	0.0017
Diesel	0.0028	0.0029	0.0031	0.0013	0.0013	0.0017
Electricity	0.0028	0.0029	0.0031	0.0013	0.0013	0.0017

In a fuel cycle or well-to-wheel (WTW) analysis, powertrain emissions along with BTW emissions together are commonly referred to as the downstream or tank-to-wheel (TTW) portion. To compute $PM_{2.5}$ TTW emissions for a gasoline or diesel light-duty vehicle in the CAFE Model, the tailpipe (TP) emissions for a given vehicle regulatory class *r*, model year *y*, and age *a* are added to the corresponding brake wear (BW) and tire wear (TW) for a vehicle of that regulatory class. Since an electric vehicle does not emit any powertrain-related exhaust, its $PM_{2.5}$ TTW emissions are simply the sum of its BW and TW components according to its regulatory class, as shown in Equation 5-14 below.

Equation 5-14: Cumulative $PM_{2.5}$ Tank-to-Wheel (TTW) Emission Calculations by Fuel Type

$$PM2.5_{r\in R,y\in Y,a\in A}{}^{gas}_{TTW} = TP^{gas}_{r,y,a} + BW_r + TW_r,$$
$$PM2.5_{r\in R,y\in Y,a\in A}{}^{diesel}_{TTW} = TP^{diesel}_{r,y,a} + BW_r + TW_r, \text{ and}$$

[825] EPA. 2020. Office of Transportation and Air Quality. *Brake and Tire Wear Emissions from Onroad Vehicles in MOVES3*. Assessment and Standards Division. pp.1-46. Available at: https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P1010M43.pdf. (Accessed: January 3, 2024).
[826] Cooley, B. 2022. CNET. America's New Weight Problem: Electric Vehicles. Published: Jan. 28 2022. Available at: https://www.cnet.com/roadshow/news/americas-new-weight-problem-electric-cars. (Accessed: Feb. 13, 2024).
[827] McTurk, E. 2022. Do Electric Vehicles Produce More Tyre and Brake Pollution Than Their Petrol and Diesel Equivalents? RAC. Available at: https://www.rac.co.uk/drive/electric-cars/running/do-electric-vehicles-produce-more-tyre-and-brake-pollution-than-petrol-and/. (Accessed: Feb. 13, 2024).

$$PM2.5_{rTTW}^{electric} = BW_r + TW_r,$$

where $r \in R$ is a chosen regulatory class in the set of three regulatory classes included in this rule (i.e., light-duty vehicle, LDT1/2a, LDT2b/3), $y \in Y$ is a chosen model year from 1975 to 2060, and $a \in A$ is a chosen age from zero to 39 years old. Brake and tire wear estimates can be revisited as more data becomes available.

To better understanding trends over time, the following visualizations of BTW emission factors were generated by regulatory class and fuel type, in terms of magnitude (Figure 5-2) and as a percentage of the total (Figure 5-3). For passenger cars, BTW particulate will constitute a slight majority of $PM_{2.5}$ emissions in 2020 and after. Similarly for light trucks, BTW will become a majority of $PM_{2.5}$ in 2035. In particular, brake wear from cars and light trucks will account for up to 40 percent of their $PM_{2.5}$ inventories by 2050.

Figure 5-2: CAFE Gasoline $PM_{2.5}$ Emission Factors Over Time by Vehicle Regulatory Class and Source

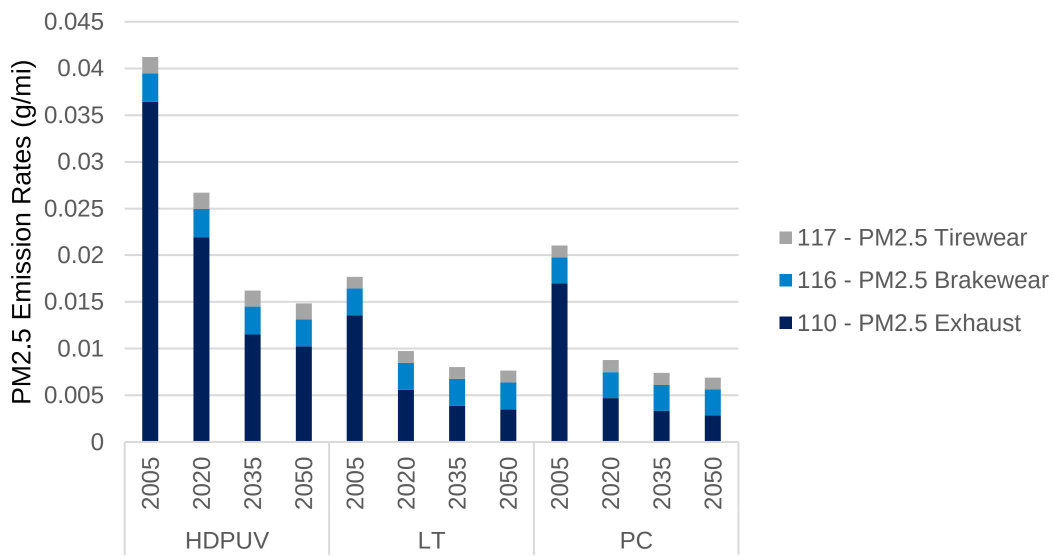
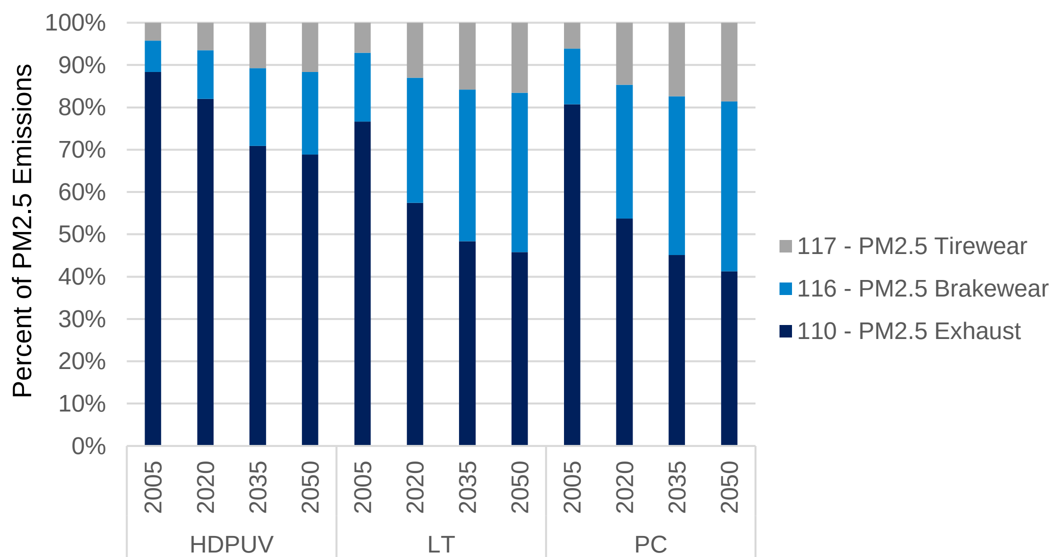


Figure 5-3: CAFE Gasoline Emission Parameters for $PM_{2.5}$ as a Percentage of Total Emissions by Regulatory Class, Source, and Evaluation Year



The next subchapter describes and helps to quantify the adverse human health impacts from both upstream and downstream vehicle emissions.

5.4. Estimating Health Impacts from Changes in Criteria Pollutant Emissions

The CAFE Model computes select health impacts resulting from population exposure to $PM_{2.5}$. associated with emissions from directly emitted particulate matter 2.5 microns or less in diameter ($PM_{2.5}$) and two precursors to $PM_{2.5}$ (NO_x and SO_2). These health impacts include several different morbidity measures, as well as two separate but equally probable mortality estimates, and are measured by the number of instances predicted to occur per ton of each PM2.5-related pollutant emitted (direct PM as well as NOx and SO2, both precursors to secondarily-formed PM2.5). The CAFE Model reports total PM2.5-related health impacts by multiplying the estimated tons of each PM2.5-related pollutant (in tons) by the corresponding health incidence per ton value. The inputs that inform the calculation of the total tons of emissions resulting from PM2.5-related pollutants are described in Chapter 5.2. This subchapter discusses how the health incidence per ton values were obtained. See Chapter 6.2.2 Monetized Health Impacts from Changes in Criteria Pollutant Emissions for information regarding the monetized damages arising from these PM2.5-related health impacts.

NHTSA's Final EIS for model years 2027 and beyond that accompanies this final rule includes a detailed discussion of the criteria pollutants and air toxics analyzed in the effects analysis. Both the Final EIS and the preamble also contain information regarding environmental justice impacts. See Chapter 8 of the FRIA for discussion of overall changes in health impacts associated with criteria pollutant changes across the different rulemaking scenarios. In addition, consistent with past analyses, NHTSA performed full-scale photochemical air quality modeling based on NPRM data and presents those results in the Final EIS. That analysis provides additional assessment of the human health impacts from changes in ambient $PM_{2.5}$ and ozone associated with the regulatory alternatives analyzed in the NPRM.

5.4.1. Health Impacts per Ton from Upstream Emissions

This subchapter describes the health incidence per ton values that are used to calculate the total health impacts from upstream criteria pollutant emissions. The health incidence per ton values in this analysis reflect the differences in health impacts arising from five upstream emission source sectors (Petroleum Extraction, Petroleum Transportation, Refineries, Fuel Transportation, Storage and Distribution, and Electricity Generation), based on publicly available EPA reports that appropriately correspond to these sectors.[828] The CAFE Model estimates health effects associated with emissions from directly emitted particulate matter 2.5 microns or less in diameter ($PM_{2.5}$) and two precursors to $PM_{2.5}$ (NO_x and SO_2). Within the same pollutant category, the differences in the incidence per ton values across different years arise from differences in the geographic distribution of the pollutants, a factor which affects the number of people impacted by the pollutants.[829]

The CAFE Model health impacts inputs are based partially on the structure of EPA's 2018 technical support document, Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors (referred to here as the 2018 EPA source apportionment TSD).[830] The 2018 EPA source apportionment TSD describes a reduced-form benefit-per-ton (BPT) approach to inform the assessment of health impacts. In this approach, the $PM_{2.5}$-related BPT values are the total monetized human health benefits (the sum of the economic value of the reduced risk of premature death and illness) that are expected from reducing one ton of directly-emitted $PM_{2.5}$ or $PM_{2.5}$ precursor such as NO_X or SO_2. We note, however, that the complex, non-linear photochemical processes that govern ozone formation prevent us from developing reduced-form ozone, ambient NO_X, or other air toxic BPT values. This is an important limitation to recognize when using the BPT approach. We include additional discussion of uncertainties in the BPT approach in Chapter 5.4.3.

Although EPA has published new health impact per ton values recently for various sectors, including refineries, oil and gas, and electricity-generating units, we have not used these in our analysis since the new

[828] For further discussion of the EPA reports used for each upstream emissions source sector, see preamble Section II.F.
[829] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. pp. 1-108. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: Feb. 13, 2024).
[830] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. pp. 1-108. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: Feb. 13, 2024).

estimates are not available for all sectors.[831] Switching to the values that use the latest EPA methodology at this time would require leaving out multiple pollutant sectors from our analysis (petroleum transportation, fuel transportation, storage, and distribution, and mobile source sectors). While the older health incidence values in our analysis slightly undervalue the benefits of reducing health emissions, removing these categories would also undervalue health emission reduction benefits.

The 2018 EPA source apportionment TSD reports benefit per ton values for the years 2016, 2020, 2025, and 2030. As the year 2016 is not included in this analysis, the 2016 values are not used. For the years in between the source years used in the input structure, the CAFE Model applies values from the closest source year. For instance, 2020 values are applied for 2022, and 2025 values are applied for 2023-2027. For further details, see the CAFE Model Documentation, which contains a description of the model's computation of monetized health impacts.

The following subchapters detail the calculations involved in mapping each CAFE Model upstream component to the appropriate sector or combination of sectors from EPA reports. Despite efforts to be as consistent as possible with the EPA sources already used in the mapping, the need to use up-to-date sources based on newer air quality modeling updates led to the use of multiple papers. Table 5-6 provides specific details of the EPA to CAFE Model upstream sector mapping.

The CAFE Model divides upstream emissions into the five varying components based on the GREET Model from Argonne National Laboratory.[832] DOT staff examined how each component was defined in GREET 2023 in order to appropriately map EPA source sectors to the ones used in the CAFE Model.

Table 5-6: CAFE/GREET Source Sectors to EPA Source Mapping

CAFE Model Upstream Component (per GREET)	Corresponding EPA Source Categories
Petroleum Extraction	Assigned to the "Oil and natural gas" sector from a 2018 EPA paper (Fann et al.).[833] Health incidents per ton were calculated using BenMAP Health Incidence Files received from EPA staff.
Petroleum Transportation	Assigned to several mobile source sectors from a 2019 EPA paper (Wolfe et al.)[834] and one source sector from the 2018 EPA source apportionment TSD.[835] The specific mode mappings are as follows: From Wolfe et al.: Rail sector (for GREET's rail mode) C1&C2 marine vessels sector (for GREET's barge mode) C3 marine vessels sector (for GREET's ocean tanker mode) On-road heavy-duty diesel sector (for GREET's truck mode) From the 2018 EPA source apportionment TSD: Electricity generating units (for GREET's pipeline mode) A weighted average of these different sectors was used to determine the overall health impact values for the sector as a whole.
Refineries	Assigned to the refineries sector in the 2018 EPA source apportionment TSD.

[831] https://www.epa.gov/system/files/documents/2021-10/source-apportionment-tsd-oct-2021_0.pdf
[832] DOE. Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) Model. Argonne National Laboratory. Last revised:Dec. 21, 2023. Available at: https://greet.es.anl.gov/. (Accessed: Feb. 13, 2024
[833] Fann et al. 2018. Assessing Human Health $PM_{2.5}$ and Ozone Impacts from U.S. Oil and Natural Gas Sector Emissions in 2025. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6718951/. (Accessed: Feb. 13, 2024).
[834] Wolfe, P. et al. 2019. Monetized Health Benefits Attributable to Mobile Source Emission Reductions Across the United States in 2025. *The Science of the Total Environment*. Vol. 650(2): pp. 2490–98. Available at: https://pubmed.ncbi.nlm.nih.gov/30296769/. (Accessed: Feb 13. 2024)(*hereinafter* Wolfe et al). Health incidence per ton values corresponding to this paper were sent by EPA staff.
[835] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. pp. 1-108. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: May 31, 2023).

Fuel TS&D	Assigned to several mobile source sectors from a 2019 EPA paper (Wolfe et al.) and one source sector from the 2018 EPA source apportionment TSD.[836] The specific mode mappings are as follows: From Wolfe et al: Rail sector (for GREET's rail mode) C1&C2 marine vessels sector (for GREET's barge mode) C3 marine vessels sector (for GREET's ocean tanker mode) On-road heavy-duty diesel sector (for GREET's truck mode) From the 2018 EPA source apportionment TSD: Electricity generating units (for GREET's pipeline mode) A weighted average of these different sectors was used to determine the overall health impact values for the sector as a whole.
Electricity Generation	Assigned to the electricity-generating units sector from the 2018 EPA source apportionment TSD.[837]

5.4.1.1. Health Incidence per Ton Values Associated with the Petroleum Extraction Sector

The basis for the health impacts from the petroleum extraction sector was a 2018 oil and natural gas sector paper (Fann et al.), which estimates health impacts for this sector in the year 2025.[838] This paper defines the oil and gas sector's emissions not only as arising from petroleum extraction but also from transportation to refineries, while the CAFE/GREET component is composed of only petroleum extraction. After consultation with the authors, it was determined that these were the best available estimates for the petroleum extraction sector, notwithstanding this difference, since they most clearly matched the category needed to map to the CAFE inputs.

Specific health incidences per pollutant were not reported in the paper, so EPA staff sent BenMAP Health Incidence Files for the oil and natural gas sector upon request. DOT staff then calculated per ton values based on these files and the tons reported in the Fann et al. paper.[839]

The only available health impacts corresponded to the year 2025. Rather than trying to extrapolate, these 2025 values were used for all the years in the CAFE Model structure: 2020, 2025, and 2030.[840] This simplification implies an overestimate of damages in 2020 and an underestimate in 2030.[841]

We understand that uncertainty exists around the contribution of VOCs to $PM_{2.5}$ formation in the modeled health impacts from the petroleum extraction sector; however, we believe that the updated health incidence values specific to petroleum extraction sector emissions may provide a more appropriate estimate of potential health impacts from that sector's emissions than the previous approach of applying refinery sector emissions impacts to the petroleum extraction sector.

[836] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. pp. 1-108. Available at: https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018. (Accessed: Feb. 13, 2024).
[837] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. pp. 1-108. Available at: https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018. (Accessed: Feb. 13, 2024).
[838] Fann, et al., 2018
[839] Nitrate-related health incidents were divided by the total tons of NO_X projected to be emitted in 2025, sulfate-related health incidents were divided by the total tons of projected SO_X, and EC/OC (elemental carbon and organic carbon) related health incidents were divided by the total tons of projected EC/OC. Both Fann et al. and the 2018 EPA source apportionment TSD define primary $PM_{2.5}$ as being composed of elemental carbon, organic carbon, and small amounts of crustal material. Thus, the BenMAP EC/OC Health Incidence Files was used for the calculation of the incidents per ton attributable to $PM_{2.5}$.
[840] These three years are used in the CAFE Model structure because it was originally based on the estimate provided in the 2018 EPA source apportionment TSD.
[841] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. pp. 1-108. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: Feb. 13, 2024).

5.4.1.2. Health Incidence per Ton Values Associated with the Petroleum Transportation Sector

The petroleum transportation sector did not correspond to any one EPA source sector, so a weighted average of multiple different EPA sectors was used to determine the health impact per ton values for the petroleum transportation sector as a whole. In calculating the weighted average, DOT staff mapped the petroleum transportation sector as described in GREET to a combination of different EPA mobile source sectors from two different papers, the 2018 EPA source apportionment TSD,[842] and a 2019 mobile source sectors paper (Wolfe et al.).[843]

Wolfe et al. include more sectors than the 2018 EPA source apportionment TSD; for instance, where 'Aircraft, Locomotive, and Marine Vessels' is a single category in the 2018 source apportionment TSD, Wolfe et al. specify four: 'Aircraft', 'Rail', 'C1&C2 Marine Vessels', and 'C3 Marine Vessels'. Therefore, sectors from Wolfe et al. are used wherever possible, and the 2018 EPA source apportionment TSD is used for the transportation mode mapping only when there are no appropriate sectors reported in the 2019 Wolfe et al. paper. Wolfe et al. only report impacts for the year 2025, but DOT staff determined that these values could be applied to the other years in the input structure.[844] Therefore, this implies a slight overestimation of health incidence per ton in 2020 and a slight underestimation of health incidence per ton in 2030.

A weighted average of these different sectors was used to calculate the total health incidences per ton by pollutant, based on the percent of upstream emissions attributable to each transportation mode.

In GREET, the model that informs the CAFE upstream component categories, there are five types of petroleum products relevant to upstream emissions for gasoline:

- Conventional crude oil
- SCO
- Dilbit
- Shale oil (Bakken)
- Shale oil (Eagle Ford)

Table 5-7: Petroleum Transportation Mode Shares in 2025[845]

Fuel Type[846]	Ocean Tanker	Barge	Pipeline	Rail	Truck
Conventional Crude Oil	2.7%	23.3%	74%	-	-
Synthetic Crude Oil (SCO)	-	-	100%	-	-
Dilbit	-	-	100%	-	-
Shale Oil (Bakken)	-	-	50%	50%	100%
Shale Oil (Eagle Ford)	-	20%	65%	15%	100%

GREET provides the expected percentage of these five petroleum products transported by each mode, as shown in Table 5-7. Transportation both within the United States and outside of U.S. borders is included, provided that the destination of the transported products is the continental United States. The percentages add up to more than 100 percent because there are multiple stages of the transportation journey. For

[842] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. pp. 1-108. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: May 31, 2023).
[843] Wolfe et al. 2019. Monetized Health Benefits Attributable to Mobile Source Emissions Reductions Across the United States in 2025. Available at: https://pubmed.ncbi.nlm.nih.gov/30296769/. (Accessed: Feb. 13, 2024).
[844] We communicated with one of the authors of the paper at EPA to help inform this decision.
[845] These values are from the GREET 2023 model, using a reference year of 2025. In the Excel version, this information can be found in the T&D Flowcharts worksheet. See https://greet.es.anl.gov/ to download the model.
[846] Conventional crude oil is both extracted domestically and imported. SCO and Dilbit are oil sand products and are imported exclusively from Canada. Shale oil is exclusively domestic. See the 'T&D Flowcharts' worksheet in the GREET model.

example, 50 percent of shale oil (Bakken) is transported by pipeline and the other 50 percent by rail during the first part of the journey to the refinery, but 100 percent of it is transported by truck on the second part of the journey.

GREET also provides emissions in grams/mmBTU of fuel transported attributable to each transportation mode. These emissions values are multiplied by the percentage of petroleum product transported by each mode, as seen in Table 5-8, to obtain a weighted value. Total emissions from each mode are used for all modes except ocean tanker. Health effects from ocean transport are concentrated in populated areas, rather than while the tankers are at sea. To address this, the ocean tanker mode includes only urban emissions. Additionally, using urban emissions for ocean tankers ensures that the emissions attributable to this mode are not underestimated, because the percentage of related health impacts decreases when using the high total emissions figure.

This process of multiplying emissions by transportation mode share is done five times, once for each of the five petroleum types. Since the transportation mode shares are projected to change over time, different weights are used for years 2020, 2025, and 2030, based on the mode percentages GREET reports for those years.[847]

Table 5-8: Energy Share by Petroleum Type[848]

Conventional Crude Oil	SCO	Dilbit	Shale (Bakken)	Shale (Eagle Ford)
79.1%	3.5%	5%	6.5%	5.9%

We multiply the energy share of each petroleum type by its corresponding emissions value to reflect how much of each emissions value should go into the weighted average. For example, using the energy share information in Table 5-8, the conventional crude emissions are multiplied by 77.3 percent, SCO emissions are multiplied by 3.7 percent, Dilbit emissions are multiplied by 5.3 percent, shale (Bakken) emissions are multiplied by 7.4 percent, and shale (Eagle Ford) emissions are multiplied by 6.2 percent.

Next, we sum the resulting weighted emissions values by pollutant to represent the total upstream emissions in grams/mmBTU of petroleum product transported. With that information, we can calculate the percentages of each pollutant attributable to each mode for petroleum transportation overall. These calculations are completed three times, for each different base year (2020, 2025, 2030). Table 5-9 shows these percentages, using base year 2025 as an example.

Table 5-9: Percent of Emissions Attributable to Each Mode for the Petroleum Transportation Category[849]

Mode	EPA source category	NO_X	SO_X	$PM_{2.5}$
Ocean Tanker	C3 marine vessels	24.05%	50.31%	37.23%
Barge	C1 & C2 marine vessels	49.66%	1.17%	30.72%
Pipeline	Electricity-generating units	18.78%	48.17%	29.51%
Rail	Rail	6.63%	0.25%	2.26%
Truck	On-road heavy-duty diesel	0.88%	0.10%	0.28%

Finally, a weighted average of health incidence is created when the percentages of emissions by mode are multiplied by the health incidence per ton from the relevant EPA sector that matches each mode. Equation 5-15 illustrates this process. The variables beginning with "%" represent the percent of SO_X emissions

[847] These are the three years used in the CAFE Model inputs for health impacts, based on the structure of the 2018 EPA source apportionment TSD that originally informed the analysis. Reference years may be changed in the 'Inputs' worksheet in the GREET model. Although the base year in the CAFE analysis is 2022, we extend the 2020 health impacts values to 2022, and use 2025 and 2030 values for subsequent years.
[848] Taken from the Petroleum tab of the GREET Excel model, using 2025 as a base year.
[849] These percentages are calculated using the 2025 base year in GREET.

attributable to each specified mode. The other variables indicate the incidents per ton resulting from SO_X emissions coming from each sector: *C3marine* corresponds to C3 marine vessels, *C1&C2* marine to C1&C2 marine vessels, *EGU* corresponds to electricity-generating units, *Rail* to railroad, and *Truck* corresponds to on-road heavy-duty diesel.

Equation 5-15: Weighted Average of Health Incidences from the Petroleum Transportation Sector

$$\textit{Asthma Exacerbation incidents per ton from SOx in Petroleum Transportation} =$$

$$(\%\ SOx\ ocean\ tanker * C3marine) + (\%\ SOx\ barge * C1\&C2\ marine) + (\%SOx\ pipeline * EGU) + (\%\ SOx\ rail * Rail) + (\%\ SOx\ truck * Truck)$$

Following guidance from the 2018 EPA source apportionment TSD, we round the incidence per ton values to two significant digits.[850]

5.4.1.3. Health Incidence per Ton Values Associated with the Fuel Transportation, Storage, and Distribution Sector

The Fuel TS&D sector, similarly to the Petroleum Transportation sector, corresponded to several different EPA source sectors, so DOT staff used the same weighted average approach as described in Chapter 5.4.1.2. Gasoline blendstocks and finished gasoline are the two components of the Fuel TS&D category described in GREET. DOT staff mapped these components to five different transportation source sectors from two EPA papers, the 2018 EPA source apportionment TSD and the 2019 mobile sources paper.[851]

GREET provides the percentage of each fuel type transported by each mode, and as in the case of the petroleum transportation calculations, the percentages change based on the year. In the case of the gasoline blendstocks fuel type, the mode shares add up to more than 100 percent because there are distinct parts of the trip and multiple modes are taken. As an example, Table 5-10 shows the estimated mode shares in 2020.

Table 5-10: Transportation Mode Shares for the Fuel TS&D Sector[852]

Mode Share	Gasoline Blendstocks	Finished Gasoline
Ocean Tanker	0.0%	0
Barge	31.2%	0
Pipeline	66.6%	0
Rail	2.2%	0
Truck	100%	100%

The emissions by pollutant attributed to each mode, measured in grams/mmBTU, are multiplied by these mode share percentages to create weighted emissions values.

Next, the weighted emissions from trucks transporting gasoline blendstocks are added to the emissions arising from finished gasoline transportation. Using that information, the total emissions per pollutant may be

[850] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. pp. 1-108. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: Feb. 13, 2024).
[851] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. pp. 1-108. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: May 31, Feb. 13, 2024); Wolfe, P. et al. 2019. Monetized health benefits attributable to mobile source emission reductions across the United States in 2025. *The Science of the Total Environment.* Vol. 650(2): pp. 2490–98. Available at: https://pubmed.ncbi.nlm.nih.gov/30296769/. (Accessed: Feb. 13, 2024).
[852] Using reference baseline year 2020 in GREET. These values can be found in the 'T&D Flowcharts' tab of the GREET model.

calculated in order to find the percentage of emissions attributable to each mode for Fuel TS&D overall. Table 5-11 provides an example of these percentages.

Table 5-11: Percent of Emissions Attributable to Each Mode for the Fuel TS&D Sector[853]

Mode	EPA category	NO_X	SO_X	$PM_{2.5}$
Ocean Tanker	C3 marine vessels	0.00%	0.00%	0.00%
Barge	C1 & C2 marine vessels	72.34%	8.52%	72.99%
Pipeline	Electricity-generating units	6.16%	79.06%	15.80%
Rail	Rail	0.86%	0.16%	0.48%
Truck	On-road heavy-duty diesel	20.64%	12.26%	10.73%

The fuel TS&D calculations follow the same process as the petroleum transportation category, matching the modes to EPA sectors and using the calculated percentages to create a weighted average of health incidence associated with emissions of each pollutant. DOT staff completed these calculations three times, for the years 2020, 2025, and 2030. As stated previously, the sectors in the 2019 mobile sources paper only showed health incidence per ton estimated for the year 2025, but we determined that this information was the most up-to-date available, after communications with the study authors. The use of 2025 health incidence for all three years implies a slight overestimation of incidences in 2020 and a slight underestimation in 2030.

5.4.1.4. Health Incidence per Ton Values Associated with the Refineries Sector

DOT staff matched the health incidence per ton values associated with the refineries sector in the 2018 EPA source apportionment TSD to the petroleum refining emission category in the CAFE Model. Table 5-12 shows the various types of health effects per ton corresponding to each pollutant emitted from the refineries sector. As discussed at the beginning of Chapter 5.4, the health effects in the CAFE Model analysis correspond to the structure of the 2018 EPA TSD, which focuses on the health effect endpoints shown in the table below.

Table 5-12: Health Incidences per Ton from the Refineries Sector

Health Effects	2020			2025			2030		
	NO_X	SO_X	$PM_{2.5}$	NO_X	SO_X	$PM_{2.5}$	NO_X	SO_X	$PM_{2.5}$
Premature Deaths - (Krewski)	0.00082	0.0082	0.039	0.00087	0.0088	0.041	0.00094	0.0095	0.044
Respiratory emergency room visits	0.00044	0.0045	0.022	0.00045	0.0047	0.023	0.00047	0.0049	0.024
Acute bronchitis	0.0012	0.012	0.059	0.0013	0.013	0.061	0.0014	0.014	0.066
Lower respiratory symptoms	0.016	0.16	0.75	0.016	0.16	0.78	0.018	0.18	0.84
Upper respiratory symptoms	0.023	0.22	1.1	0.023	0.23	1.1	0.025	0.25	1.2
Minor Restricted Activity Days	0.66	6.7	31	0.67	6.8	32	0.68	7.0	33
Work loss days	0.11	1.1	5.3	0.11	1.2	5.4	0.12	1.2	5.6
Asthma exacerbation	0.026	0.26	1.2	0.027	0.28	1.3	0.029	0.29	1.4

[853] Calculated using year 2025 in GREET.

Cardiovascular hospital admissions	0.00019	0.0021	0.0095	0.00022	0.0023	0.010	0.00024	0.0026	0.012
Respiratory hospital admissions	0.00019	0.0020	0.0089	0.00021	0.0022	0.010	0.00024	0.0025	0.011
Non-fatal heart attacks (Peters)	0.00080	0.0082	0.038	0.00088	0.0091	0.041	0.00097	0.010	0.045
Non-fatal heart attacks (All others)	0.000087	0.00089	0.0041	0.000095	0.00099	0.0045	0.00010	0.0011	0.0049

5.4.1.5. Health Incidence per Ton Values Associated with the Electricity Generation Sector

The 2018 EPA source apportionment TSD contains health incidence per ton values associated with emissions of NO_X, SO_X, and $PM_{2.5}$ arising from electricity-generating units. DOT staff mapped these to the electricity generation emission source sector in the CAFE Model. The health effects per ton associated with the emissions of criteria pollutants from this sector are shown in Table 5-13.

Table 5-13: Health Incidences per Ton from the Refineries Sector

Health Effects	2020			2025			2030		
	NO_X	SO_X	$PM_{2.5}$	NO_X	SO_X	$PM_{2.5}$	NO_X	SO_X	$PM_{2.5}$
Premature Deaths - (Krewski)	0.00066	0.0045	0.016	0.00070	0.0048	0.017	0.00074	0.0051	0.018
Respiratory emergency room visits	0.00032	0.0022	0.0091	0.00033	0.0023	0.0094	0.00034	0.0024	0.0098
Acute bronchitis	0.00085	0.0055	0.021	0.00089	0.0057	0.022	0.00096	0.0062	0.024
Lower respiratory symptoms	0.011	0.070	0.27	0.011	0.073	0.29	0.012	0.079	0.31
Upper respiratory symptoms	0.016	0.10	0.39	0.016	0.10	0.41	0.017	0.11	0.44
Minor Restricted Activity Days	0.46	3.0	12	0.46	3.0	12	0.46	3.1	12
Work loss days	0.077	0.51	2.0	0.077	0.52	2.0	0.078	0.53	2.1
Asthma exacerbation	0.018	0.12	0.46	0.019	0.12	0.48	0.020	0.13	0.51
Cardiovascular hospital admissions	0.00016	0.0011	0.0040	0.00017	0.0012	0.0044	0.00018	0.0014	0.0048
Respiratory hospital admissions	0.00015	0.0011	0.0038	0.00017	0.0012	0.0043	0.00018	0.0013	0.0047

Non-fatal heart attacks (Peters)	0.00063	0.0045	0.016	0.00068	0.0049	0.018	0.00074	0.0053	0.019
Non-fatal heart attacks (All others)	0.000068	0.00049	0.0017	0.000074	0.00054	0.0019	0.000079	0.00058	0.0021

5.4.2. Health Impacts per Ton from Vehicle-Based Emissions

The CAFE Model follows a similar process for computing health impacts resulting from vehicle-based (downstream) emissions as it does for calculating health impacts from upstream emissions. The analysis relies on a 2019 paper (Wolfe et al.) that computes monetized per ton damage costs for mobile sources in several categories, based on vehicle type and fuel type. Wolfe et al. did not report incidences per ton, but that information was obtained through communications with EPA staff.

We matched three source categories from the Wolfe et al. paper to the CAFE Model light-duty vehicle downstream emissions inventory: "on-road LD gas cars and motorcycles," "on-road LD gas trucks," and "on-road LD diesel."[854] To account for heavy-duty pickup truck and van-based emissions, we applied the health impact categories for heavy-duty diesel and heavy-duty gas vehicle emissions.

5.4.3. Uncertainty

Uncertainties and limitations exist at each stage of the emissions-to-health benefit analysis pathway (e.g., projected emissions inventories, air quality modeling, health impact assessment, economic valuation). We used a BPT approach to estimate health impacts from changes in criteria pollutant emissions and the resulting monetized benefits, which are discussed further in Chapter 6.2.2, Monetized Health Impacts from Changes in Criteria Pollutant Emissions. The following discussion applies to that subchapter as well.

The BPT approach to monetizing benefits relies on many assumptions; when uncertainties associated with these assumptions are compounded, even small uncertainties can greatly influence the size of the total quantified benefits. Some key assumptions associated with $PM_{2.5}$-related health benefits and uncertainties associated with the BPT approach are described below.

We assume all fine particles, regardless of chemical composition, are equally potent in causing premature mortality. Support for this assumption comes from the 2019 PM ISA, which concluded that "many $PM_{2.5}$ components and sources are associated with many health effects and that the evidence does not indicate that any one source or component is consistently more strongly related with health effects than $PM_{2.5}$ mass."[855]

We assume that the health impact function for fine particles is log-linear without a threshold. Thus, the estimates include health benefits from reducing fine particles in areas with different concentrations of $PM_{2.5}$, including both areas with projected annual mean concentrations that are above the level of the fine particle standard and areas with projected concentrations below the level of the standard.

We also assume that there is a "cessation" lag between the change in PM exposures and the total realization of changes in mortality effects. Specifically, we assume that some of the incidences of premature mortality related to $PM_{2.5}$ exposures occur in a distributed fashion over the 20 years following exposure based on the advice of the Science Advisory Board Health Effect Subcommittee,[856] which affects the valuation of mortality benefits at different discount rates. The above assumptions are subject to uncertainty.

In general, we are more confident in the magnitude of the risks we estimate from simulated $PM_{2.5}$ concentrations that coincide with the bulk of the observed PM concentrations in the epidemiological studies

[854] Wolfe, P. et al. 2019. Monetized Health Benefits Attributable to Mobile Source Emission Reductions Across the United States in 2025. *The Science of the Total Environment.* Vol. 650(2): pp. 2490–98. Available at: https://pubmed.ncbi.nlm.nih.gov/30296769/. (Accessed: Feb. 13, 2024).
[855] EPA. 2019. Integrated Science Assessment (ISA) for Particulate Matter (Final Report, 2019). U.S. Environmental Protection Agency: Washington, D.C. EPA/600/R-19/188.
[856] EPA. 2004. Advisory Council on Clean Air Compliance Analysis Response to Agency Request on Cessation Lag. EPA-COUNCIL-LTR-05-001. Located in Docket ID NHTSA-2021-0053.

that are used to estimate the benefits. Likewise, we are less confident in the risk we estimate from simulated $PM_{2.5}$ concentrations that fall below the bulk of the observed data in these studies. There are uncertainties inherent in identifying any particular point at which our confidence in reported associations decreases appreciably, and the scientific evidence provides no clear dividing line. Applying BPT values to estimates of changes in policy-related emissions precludes us from assessing the distribution of risk as it relates to the associated distribution of reference baseline concentrations of $PM_{2.5}$.

Another limitation of using the BPT approach is an inability to provide estimates of the health benefits associated with exposure to ozone, ambient NO_X, and air toxics. Furthermore, the air quality modeling that underlies the $PM_{2.5}$ BPT value did not provide estimates of the $PM_{2.5}$-related benefits associated with reducing VOC emissions, but these unquantified benefits are generally small compared to benefits associated with other $PM_{2.5}$ precursors.[857]

National-average BPT values reflect the geographic distribution of the underlying modeled emissions used in their calculation, which may not exactly match the geographic distribution of the emission reductions that would occur due to a specific rulemaking. Similarly, BPT estimates may not reflect local variability in population density, meteorology, exposure, reference baseline health incidence rates, or other local factors for any specific location. For instance, even though we assume that all fine particles have equivalent health effects, the BPT estimates vary across precursors depending on the location and magnitude of their impact on $PM_{2.5}$ levels, which drives population exposure. The emissions and photochemically-modeled $PM_{2.5}$ concentrations used to derive the BPT values may not match the changes in air quality that would result from this rule.

[857] EPA. 2012. Regulatory Impact Analysis for the Proposed Revisions to the National Ambient Air Quality Standards for Particulate Matter. Located in Docket ID NHTSA-2017-0069-0344.

6. Simulating Economic Effects of Regulatory Alternatives

6.1. Costs and Benefits to Consumers and Commercial Operators

CAFE Model Files Referenced in this Chapter

Below is a list of CAFE Model Files referenced in this chapter. See Chapter 2.1.9 "Where to Find the Internal NHTSA Files?" for a full list of files referenced in this document and their respective file locations.

- Market Data Input File
- Parameters Input File
- CAFE Model Documentation

Many of the benefits and costs resulting from changes to CAFE standards for light-duty vehicle and fuel efficiency standards for HDPUV vehicles are private impacts that accrue to the buyers of new cars and trucks produced in the affected model years. These benefits and costs are primarily attributable to the changes in vehicle ownership and operating costs that result from improved fuel economy and efficiency, and the cost of the technology required to achieve those improvements. In general, increasing standards cause manufacturers to apply additional technology to the new vehicles they produce and offer for sale, so that they comply with the new standards. These technologies increase the cost of producing vehicles, and manufacturers pass those cost increases along to consumers in the form of higher purchase prices. In turn, the higher purchase prices that buyers of new cars and light trucks pay also mean that their expenses for sales taxes, vehicle registration fees, and insurance on their new vehicles will rise. At the same time, initial buyers and subsequent owners of those vehicles experience reduced fuel costs over the vehicles lifetimes and save time from less frequent refueling.

6.1.1. Additional Consumer Purchasing Costs

Some costs of purchasing and owning new vehicles increase in proportion to their purchase prices. When fuel economy standards increase the price of new vehicles, both taxes and registration fees increase, because these are both typically calculated as a percentage of vehicle price. Increasing the price of new vehicles also affects the average amount paid on insurance premiums for similar reasons. NHTSA computes these additional costs as scalar multipliers on the MSRP of new vehicles. These costs are included in the agency's consumer per-vehicle cost-benefit analysis but, for the reasons described below, are not included in the societal cost-benefit analysis.

6.1.1.1. Sales Taxes and Vehicle Registration Costs

In the analysis, sales taxes and registration fees are considered transfer payments between consumers and the government and are therefore do not represent real economic costs from the societal perspective. However, these do represent additional costs to consumers and are accounted for when viewing the impacts of raising standards from the perspective of private consumers. To estimate the sales tax for the analysis, NHTSA weighted the sales tax each state imposes on purchases of new vehicles by its population—using Census population data—to calculate a national weighted-average sales tax of 5.46 percent.[858]

We recognize that weighting state sales tax by new vehicle purchases within a state would likely produce a better estimate, since new vehicle purchasers represent a small subset of the population, and this relationship may differ between states. NHTSA explored using Polk registration data to approximate new vehicle sales by state by examining the change in new vehicle registrations across several recent years. The results derived from this examination resulted in a national weighted-average sales tax rate slightly above 5.5 percent, almost identical to the rate calculated using population instead. NHTSA opted to utilize the population-weighted

[858] See Car Tax by State at: http://www.factorywarrantylist.com/car-tax-by-state.html. (Accessed: Feb. 14, 2024). Note: County, city, and other municipality-specific taxes were excluded from weighted averages, as the variation in locality taxes within states, lack of accessible documentation of locality rates, and lack of availability of weights to apply to locality taxes complicate the ability to reliably analyze the subject at this level of detail. Localities with relatively high automobile sales taxes may have relatively fewer auto dealerships, as consumers would endeavor to purchase vehicles in areas with lower locality taxes, therefore reducing the effect of the exclusion of municipality-specific taxes from this analysis.

estimate, rather than the registration-based proxy of new vehicle sales, because the results were negligibly different, and the analytical approach was more straightforward and easily reproducible.

6.1.1.2. Insurance Costs

More expensive vehicles will require more expensive collision and comprehensive (e.g., fire and theft) car insurance. Actuarially fair insurance premiums for these components of value-based insurance will be the amount an insurance company will pay out in the case of an incident weighted by the risk of its occurrence. For simplicity, we assume that the vehicle has the same exposure to harm throughout its lifetime in this calculation. However, the value of vehicles will depreciate at some rate so that the absolute amount paid in value-related insurance will decline as the vehicle depreciates. This is represented in the CAFE Model as Equation 6-1, which is used to calculate the stream of expected collision and comprehensive insurance payments. The agency reduces insurance costs by 20 percent to account for the additional benefit consumers associated with higher payouts in the event the vehicle is totaled.[859]

Equation 6-1: Estimating Insurance Costs

$$(Comprehensive\ \&\ Collision)_{age} = \frac{MSRP^{*}(share\ MSRP)}{(1+depreciation\ )^{age}} * (1-0.20)$$

To utilize the framework described by Equation 6-1, estimates of the share of MSRP paid on collision and comprehensive insurance and of annual vehicle depreciation rates are needed. Wards Automotive has data on the average annual amount paid by model year for new light trucks and passenger cars on collision, comprehensive and damage and liability insurance for model years 1992-2003; for model years 2004-2016, however, Ward's only reports the total amount paid for insurance premiums. The share of total insurance premiums paid for collision and comprehensive insurance coverage throughout the lifetime of a vehicle was computed for 1979-2003. For cars, this share ranges from 49 to 55 percent of total insurance premiums, with the share tending to be largest towards the end of the series. For trucks, the share ranges from 43 to 61 percent of total insurance premiums, again, with the share increasing towards the end of the series.

We assume that for model years 2004-2016, 60 percent of insurance premiums for trucks, and 55 percent for cars, is paid for collision and comprehensive coverage. Using these shares, we computed the aggregate amount paid for collision and comprehensive coverage for cars and trucks. Then each regulatory class in the fleet is weighted by share to estimate the overall average amount paid for collision and comprehensive insurance by model year as shown in Table 6-1. The ratio of annual collision and comprehensive costs to average MSRP results in a range from 1.74 to 2.03 percent over the series. The average annual share paid for model years 2010-2016 is 1.83 percent of the initial MSRP. This is used as the share of the value of a new vehicle paid for collision and comprehensive in the future, or "share MSRP" in Equation 6-1.

Table 6-1: Average Share of MSRP Paid for Collision and Comprehensive Insurance

Model Year	Annual Collision and Comprehensive Insurance Payments	Average MSRP	Share MSRP
2016	$681	$33,590	2.03%
2015	$601	$32,750	1.84%
2014	$567	$31,882	1.78%
2013	$548	$31,056	1.76%
2012	$530	$30,062	1.76%
2011	$517	$29,751	1.74%

[859] Industry reports indicate 19.1 percent of all car insurance claims are for totaled or stolen vehicles, see https://www.repairerdrivennews.com/2019/06/18/ccc-q1-data-claim-counts-down-nearly-1-severity-total-loss-valueup. (Accessed: May 20, 2024).

2010	$548	$29,076	1.88%

To estimate depreciation rates, we used recent data from Black Book and Fitch,[860] which showed that the average annual depreciation rate of two- to six-year-old vehicles fluctuated over the last decade from a high of 17.3 percent to a low of 8.3 percent[861] prior to the pandemic. The pandemic rates are unlikely to be representative of future depreciation rates, so we averaged the annual rates from 2016 – 2019 to construct a more representative average depreciation rate (14.9 percent). We assume that future depreciation rates will resemble pre-pandemic trends as the pandemic continues to recede, and the analysis assumes the same depreciation rate for all future years.

Table 6-2 shows the cumulative share of the initial MSRP of a vehicle estimated to be paid in collision and comprehensive insurance in five-year age increments under this depreciation assumption, conditional on a vehicle surviving to that age—that is, the expected insurance payments at the time of purchase will be weighted by the probability of surviving to that age. If a vehicle lives to 10 years, 10.6 percent of the initial MSRP is expected to be paid in collision and comprehensive payments; by 20 years 13.2 percent of the initial MSRP; finally, if a vehicle lives to age 40, 14.1 percent of the initial MSRP.

Table 6-2: Cumulative Percentage of MSRP Paid in Collision/Comprehensive Premiums by Age

Age	Percentage of Value Remaining	Cumulative Percentage of MSRP Paid
5	64%	7.0%
10	32%	10.6%
15	16%	12.4%
20	8.0%	13.2%
25	4.0%	13.7%
30	2.0%	13.9%
35	1.0%	14.0%
40	0.5%	14.1%

The increase in insurance premiums resulting from an increase in the average value of a vehicle reflects an increase in the expected amount insurance companies will have to pay out in the case of damage occurring to the driver's vehicle. In this way, it becomes a cost to the private consumer that is attributable to the higher standards, since raising the standard caused the increase in insurance costs through higher vehicle purchasing prices.

NHTSA notes that insurance premiums are important to track in the per-vehicle analysis to the extent that standards make new vehicles more expensive, which presumably make them more expensive to repair following a collision. These payments to consumers to replace higher cost vehicles in more stringent cases should be higher, which is a benefit to consumers that is not captured in our analysis. To avoid inappropriately including an insurance cost without accounting for the consumer benefit of higher payouts in the event the original vehicle is totaled or stolen, we multiply insurance costs by the percentage of insurance claims for vehicle repairs, which excludes claims for totaled and stolen vehicles. This approach is conservative because the cost to replace a vehicle is higher than the cost to repair a vehicle, so the share of insurance outlays that cover replacements will be higher than the percentage of claims for totaled or stolen

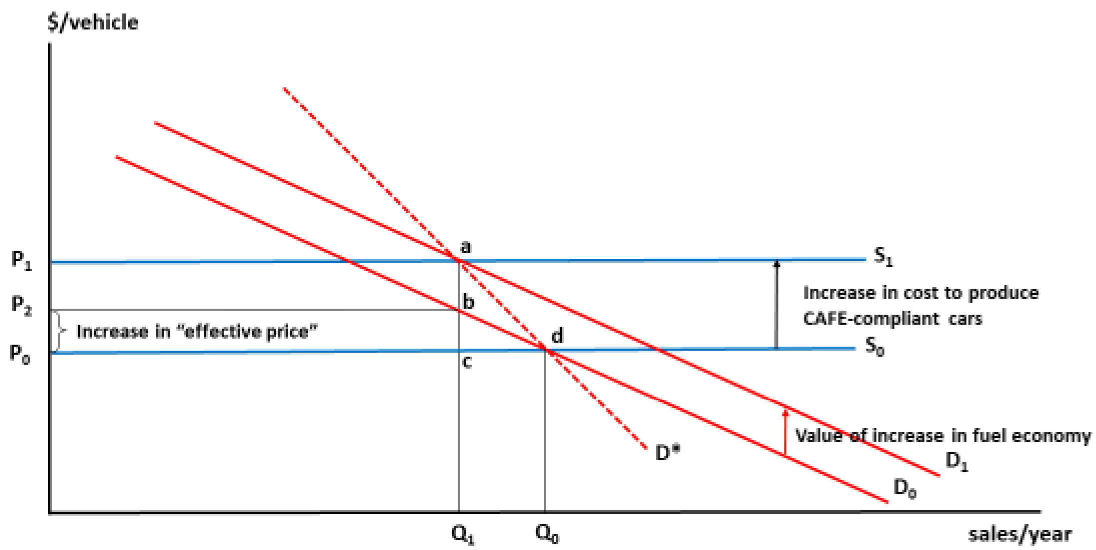
[860] Vehicle Depreciation Report. 2021. Black Book and Fitch Ratings. Available at: https://www.blackbook.com/black-book-fitch-ratings-release-2021-joint-vehicle-depreciation-report/. (Accessed: Feb. 14, 2024).
[861] During the pandemic depreciation largely halted, with two- to six-year old vehicles depreciating at only 2 percent in 2020 and projected at only 5 percent in 2021.

vehicles. Based on NHTSA's research, the percentage of claims for replacing totaled or stolen vehicles is 20 percent.[862]

6.1.2. Losses in Consumer Surplus from Reduced Sales

Buyers who would have purchased a new vehicle with the baseline standards in effect but decide not to do so when new vehicles' prices increase due to more stringent CAFE and fuel efficiency standards experience a reduction in welfare. The collective welfare loss to potential buyers who are deterred by higher prices is measured by the foregone consumer surplus they would have received from their purchase of a new vehicle in the baseline. However, because the fuel economy of vehicles they would otherwise have purchased also increases, and higher fuel economy would have provided some value to them, measuring their loss in consumer surplus is more complicated than in the conventional case where the price of a product changes but its other attributes do not.[863]

Figure 6-1: New Vehicle Consumer Surplus



The triangle bcd in Figure 6-1 reflects the loss of consumer surplus to new vehicle buyers, calculated based on changes to new vehicle sales. In the figure, P_0 reflects the baseline vehicle cost, and adopting higher CAFE and fuel efficiency standards raises the cost of producing vehicles from S_0 to S_1 and increases their selling price to P_1. Consistent with other subchapters of the analysis, however, we assume that consumers value 30 months of fuel savings at the time they purchase new vehicles. The value of these savings, which is reflected by an upward shift the demand curve from D_0 to D_1, offsets part of the price increase, thus reducing new vehicles' "effective" purchase price from P_1 to P_2. This shift leads the number sold to decline from Q_0 to Q_1, but this represents a smaller decline in sales than would have occurred without the improvement in fuel economy. The dashed line D* is a linear representation of the change in quantity of vehicles purchased.[864] The loss in consumer surplus to would-be buyers of the new vehicles that are no longer sold included in NHTSA's analysis of societal costs is equal to the area of triangle bcd.[865]

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[862] Huetter, J. 2019. Repairer Driven News: CCC Q1 Data: Claim Counts Down Nearly 1%; Severity, Total Loss Value Up. Available at: https://www.repairerdrivennews.com/2019/06/18/ccc-q1-data-claim-counts-down-nearly-1-severity-total-loss-value-up/. (Accessed: Feb. 14, 2024).

[863] Consumer surplus is a fundamental economic concept and represents the net value (or net benefit) a good or service provides to consumers. It is measured as the difference between what a consumer is willing to pay for a good or service and the market price. OMB Circular A-4 explicitly identifies consumer surplus as a benefit that should be accounted for in cost-benefit analysis. For instance, OMB Circular A-4 states the "net reduction in total surplus (consumer plus producer) is a real cost to society," and elsewhere elaborates that consumer surplus values be monetized "when they are significant." OMB Circular A-4, at pp. 37–8.

[864] D* is not itself a demand curve, because the "quality" of vehicles changes with movements along it. It is included in Figure 6-1 to help visualize the change in consumer welfare.

[865] The exact calculation is half the increase in sales multiplied by the reduction in the cost of light-duty vehicles net of the increased fuel cost.

6.1.3. Value of Fuel Savings

Fuel savings are calculated by multiplying the savings in fuel consumption that result from sales and use of higher-mpg vehicles by fuel prices. Each vehicle of a given body style within an alternative is assumed to be driven the same distance as others in that alternative of comparable age and body style in each calendar year. Dividing a vehicle's annual mileage by its average fuel economy yields an estimate of its average yearly fuel consumption. The difference between total fuel consumption in the baseline and under each alternative, represents the gallons (or energy) saved. Under this assumption, our estimates of fuel consumption from increasing the fuel economy of each individual model depend only on how much its fuel economy is increased, and do not reflect whether its actual use differs from other models of the same body type. Neither do our estimates of fuel consumption account for variation in how much vehicles of the same body type and age are driven each year, which appears to be significant (see Chapter 4.3.1).

Consumers save money on fuel expenditures at the average retail fuel price which includes all taxes (fuel price assumptions are discussed in detail in Chapter 4.1.2). For gasoline and diesel, the included taxes reflect both the federal tax and a calculated average state fuel tax. Expenditures on alternative fuels (E85 and electricity, primarily) are also included in the calculation of fuel expenditures on which fuel savings are based. And while the included taxes net out of the social benefit cost analysis (as they are a transfer from vehicle users to government agencies), consumers value each gallon saved at retail fuel prices including any additional fees such as taxes.

Assuming each vehicle is driven the average miles for its cohort—body style and age in any given calendar year—may lead to an underestimation of fuel consumption under more stringent standards. Because the distribution of annual driving is wide, using its mean value to estimate fuel savings for individual car or light truck models may overstate the fuel consumption likely to result under tighter standards, even when the fuel economy values of different models are correctly averaged.[866] This will be the case even when increases in fuel economy can be estimated reliably for individual models, which this analysis does, because the reduction in a specific model's fuel consumption depends on how much it is actually driven as well as on the change in fuel economy or efficiency under alternative standards.

To illustrate, we estimate that new automobiles are driven about 17,000 miles on average during their first year.[867] If the 17,000 mile figure represents the average of two different models that are driven 14,000 and 20,000 miles annually, and the two initially achieve, respectively, 30 and 40 miles per gallon—thus averaging 35 miles per gallon—they will consume a total of 967 gallons annually.[868] Improving the fuel economy of each model by 5 miles per gallon will reduce their total fuel use to 844 gallons, thus saving 123 gallons annually.[869] In contrast, using the 17,000 mile average figure for both two vehicles yields estimated fuel savings of 128 gallons per year, about 4 percent above the correct value.[870]

The magnitude of this potential overestimation of fuel savings increases with any association between annual driving and fuel economy. Purchasers who anticipate driving more are presumably more likely to choose models offering higher fuel economy, because the number of miles driven directly affects their fuel costs and thus the savings they obtain from driving a model that features higher fuel economy.[871] Conversely, buyers who anticipate driving less are likely to purchase models with lower fuel economy. Such behavior— whereby

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[866] The correct average fuel economy of vehicles whose individual fuel economy differs is the harmonic average of their individual values, weighted by their respective use; for two vehicles with fuel economy levels MPG_1 and MPG_2 that are assumed to be driven identical amounts (as in the agencies' analysis), their harmonic average fuel economy is equal to $2/(1/MPG_1 + 1/MPG_2)$.
[867] While the mileage accumulation schedule reflects this estimate, the actual VMT during 2020 (and the next few subsequent years) is lower, as U.S. light-duty VMT declined significantly during the pandemic.
[868] Calculated as 14,000 miles / 30 miles per gallon + 20,000 miles / 40 miles per gallon = 467 gallons + 500 gallons = 967 gallons (all figures in this calculation are rounded to whole gallons).
[869] Calculated as 14,000 miles / 35 miles per gallon + 20,000 miles / 45 miles per gallon = 400 gallons + 444 gallons = 844 gallons (again, all figures in this calculation are rounded to whole gallons).
[870] Our estimate of their combined initial fuel consumption would be 17,000 miles / 30 miles per gallon + 17,000 miles / 40 miles per gallon, or 567 gallons + 425 gallons = 992 gallons. After the 5 mile per gallon improvement in fuel economy for each vehicle, our estimate would decline to 17,000 miles / 35 miles per gallon + 17,000 miles / 45 miles per gallon = 486 + 378 = 863 gallons, yielding an estimated fuel savings of 992 gallons - 863 gallons = 128 gallons (as previously, all figures in this calculation are rounded to whole gallons).
[871] For example, some businesses, rental car firms, taxi operators, and ride sharing drivers are likely to anticipate using their vehicles significantly more than the average new car or LT buyer. Furthermore, their choices among competing models are likely to be more heavily influenced by economics than by the preferences for other attributes that motivate many other buyers, making them more likely to select vehicles with higher fuel economy in order to improve their economic returns.

buyers who expect to drive more extensively are likely to select models offering higher fuel economy—cannot be fully accounted for in this analysis, which is necessarily based on empirical estimates of average vehicle use. To the extent it occurs, we are likely to consistently overstate actual fuel savings from requiring higher fuel economy. Thus, it is possible we overestimate the impact on consumer and social benefits such as reduced fuel consumption and increased refueling time, as well as on the resulting environmental impacts of fuel production and use.

A similar phenomenon may cause the analysis to overstate the *value* of fuel savings resulting from requiring higher standards as well. As with miles driven, our analysis assumes all vehicle owners pay the national average fuel price at any time. However, fuel prices vary substantially among different regions of the United States, and one would expect buyers in regions with consistently higher fuel prices to purchase vehicles with higher fuel economy, on average. To the extent they do so, evaluating the savings from requiring higher standards identically in all regions using nationwide average fuel prices is likely to overstate their actual dollar value.

As an illustration, suppose gasoline averages $3.00 per gallon nationwide, but a buyer who expects to drive a new car 17,000 miles during its first year (the same value used in the example above) faces a local price of $4.00 per gallon, and chooses a model that achieves 40 mpg. That driver's cost of fuel during the vehicle's first year will total $1,700 (calculated as 17,000 miles / 40 miles per gallon x $4.00 per gallon). A buyer who plans to drive the same number of miles but faces a lower price of $2.00 per gallon and thus chooses a vehicle that offers only 30 mpg will have first-year fuel costs of $1,133 (calculated as 17,000 miles / 30 miles per gallon x $2.00 per gallon), so total annual fuel costs for these two vehicles will be $1,700 + $1,133 = $2,633. If the fuel economy of both vehicles increases by 5 mpg, their actual fuel savings will be $189 and $162, or a total savings of $351. However, evaluating total fuel savings using a price of $3.00 per gallon yields savings of $382, thus overstating their actual combined savings by almost 9 percent.

6.1.4. Benefits of Fewer Frequent Refueling Events

Increasing standards affects the amount of time drivers spend refueling their vehicles in several ways. First, higher standards increase the fuel economy or fuel efficiency of ICE vehicles produced in the future, which increases vehicle range and decreases the number of refueling events for those vehicles. Second, to the extent that more stringent standards increase the purchase price of new vehicles, they may reduce sales of new vehicles and retirement of used ones, in turn causing more VMT to be driven by older and less efficient vehicles which require more frequent refueling for the same amount of use. The basic calculation for all three effects is the same: we multiply the additional amount of time spent refueling by the collective value of time for vehicles' occupants, which is assumed to be the same for all three effects.

6.1.4.1. Value of Travel Time Savings

The calculation of the value of time follows the guidance from DOT's 2016 *Value of Travel Time Savings* memorandum ("VTTS Memo").[872] The economic value of refueling time savings is calculated by applying valuations for travel time savings from the VTTS Memo to estimates of how much time is saved across alternatives.[873] The value of travel time depends on average hourly valuations of personal and business time, which are functions of annual household income and total hourly compensation costs to employers, respectively. As designated by the 2016 VTTS memo, the nationwide median annual household income, $56,516 in 2015, is divided by 2,080 hours to yield an income of $27.20 per hour (rounded to the nearest ten cents). Total hourly compensation cost to employers, inclusive of benefits, in 2015 was $25.40.[874]

Table 6-3 demonstrates NHTSA's approach to estimating the value of travel time ($/hour) for urban and rural driving; we make the simplifying assumption that urban travel consists entirely of local trips, while travel in rural areas is exclusively longer-distance intercity travel. This approach relies on the use of DOT-recommended weights that assign a lesser valuation to personal travel time than to business travel time, as

[872] DOT. 2016. The Value of Travel Time Savings: Departmental Guidance for Conducting Economic Evaluations. Revision 2. Departmental Guidance on Valuation of Travel Time in Economic Analysis. Available at: https://www7.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-valuation-travel-time-economic. (Accessed: Feb. 14, 2024).
[873] VTTS Memo Tables 1, 3, and 4.
[874] *Ibid* at 15.

well as weights that adjust for the distribution between personal and business travel.[875] In accordance with DOT guidance, wage valuations are estimated with base year 2015 dollars and end results are adjusted to 2022 dollars.

Table 6-3: Estimating the Value of Travel Time for Urban and Rural (Intercity) Travel ($/hour, 2015 Dollars)

	Personal Travel	Business Travel	Total
Urban Travel			
Wage Rate ($/hour)	$27.20	$25.40	-
DOT - Recommended Value of Travel Time Savings, as % of Wage Rate	50%	100%	-
Hourly Valuation (= Wage Rate * DOT-Recommended Value)	$13.60	$25.40	-
% of Total Urban Travel	95.4%	4.6%	100%
Contribution to Total Hourly Valuation (Adjusted for % of Urban Travel)	$13.00	$1.20	$14.10
Rural (Intercity) Travel			
Wage Rate ($/hour)	$27.20	$25.40	
DOT - Recommended Value of Travel Time Savings, as % of Wage Rate	70%	100%	
Hourly Valuation (= Wage Rate * DOT-Recommended Value)	$19.00	$25.40	
% of Total Rural Travel	78.6%	21.4%	100%
Contribution to Hourly Valuation (Adjusted for % of Total Rural Travel)	$15.00	$5.40	$20.40

Estimates of the hourly value of urban and rural travel time ($14.10 and $20.40, respectively), shown in Table 6-3, must then be adjusted to account for the nationwide ratio of urban to rural driving.[876] This adjustment, which gives an overall estimate of the hourly value of travel time — independent of urban or rural status — is shown in Table 6-4.

Table 6-4: Estimating Weighted Urban/Rural Value of Travel Time ($/hour, 2015 Dollars)

	Unweighted Value of Travel Time ($/hour)	Weight (% of Total Miles Driven)	Weighted Value of Travel Time ($/hour)
Urban Travel	$14.10	71.6%	$10.10

[875] Business travel is higher than personal travel because an employer has additional expenses, e.g. taxes and benefits costs, above and beyond an employee's hourly wage.
[876] Federal Highway Administration. 2021. Estimate of Urban vs. Rural travel weights from FHWA Highway Statistics. 2019. Table VM-1 (light-duty vehicles only): Annual vehicle distance traveled. Available at: https://www.fhwa.dot.gov/policyinformation/statistics/2019/pdf/vm1.pdf. (Feb. 14, 2024).

Rural Travel	$20.40	28.4%	$5.80
Total	-	100.0%	$15.90

Note that the calculations in Table 6-4 represent the hourly value of travel time for each individual vehicle occupant, and many vehicles have multiple occupants. To estimate the average value of travel time per vehicle-hour, Table 6-5 accounts for all passengers in vehicles making refueling stops. We estimated average vehicle occupancy using data from the 2017 National Household Travel Survey, and our estimate of average vehicle occupancy includes the driver and all passengers who are age five and above.[877] The average occupancy assumption used in the refueling benefit is consistent with occupancy assumptions used to estimate the social cost of additional traffic congestion.

Table 6-5: Estimating the Value of Travel Time for Light-Duty Vehicles ($/hour, 2015 Dollars)

	Passenger Cars	Light Trucks
Average Vehicle Occupancy During Refueling Trips (persons)	1.52	1.83
Weighted Value of Travel Time ($/hour)	$15.90	$15.90
Occupancy-Adjusted Value of Vehicle Travel Time During Refueling Trips ($/hour)	$24.20	$29.10

Lastly, the occupancy-adjusted value of travel time per vehicle-hour is converted to 2021 dollars using the GDP deflator as shown in Table 6-6.[878] Although estimates have been calculated for both passenger cars and light trucks (CAFE LDV), this analysis uses light truck estimates as the most approximate application for heavy-duty pick-ups and vans.

Table 6-6: Value of Vehicle Travel Time in 2021 Dollars ($/hour, 2021 Dollars)

	Passenger Cars	Light Trucks
Occupancy-Adjusted Value of Vehicle Travel Time During Refueling Trips ($/hour)	$27.50	$33.10

6.1.4.2. Accounting for Improved Fuel Economy of ICE Vehicles

The CAFE Model calculates the number of refueling events for each ICE vehicle in a calendar year – calculated as the number of miles driven by each vehicle in that calendar year divided by the product of that vehicle's on-road fuel economy (rather than fuel economy as measured for compliance), tank size, and an assumption about the average share of the tank refueled at each event, as shown in Equation 6-2.

Equation 6-2: Calculating the Number of Refueling Events

$$\mathit{Refuel\ Events}_{CY,\ Veh}=\frac{\mathit{Miles}_{CY,\ Veh}}{FE_{Veh}*\mathit{Tank}_{Veh}*\mathit{Share}_{Veh}}$$

The model then computes the cost of refueling – the product of the number of refueling events, total time of each event, and the value of the time spent on each event (computed as average salary), as shown in Equation 6-3.

[877] The National Household Travel Survey excludes trips by children under age five.
[878] Bureau of Economic Analysis (BEA). 2023.National Income and Product Accouns (NIPA) NIPA Table 1.1.9 Implicit Price Deflators for Gross Domestic Product. Available at https://apps.bea.gov/iTable/?reqid=19&step=2&isuri=1&categories=survey. (Accessed: Feb. 14, 2024).

Equation 6-3: Calculating the Cost of Refueling Events

$$Cost_{CY,Veh}=Refuel\ Events_{CY,\ Veh}*(Event\ Time_{Veh})*Time\ Value$$

The refueling event time of each vehicle is calculated by summing a fixed and variable component. The fixed component is the number of minutes required for each refueling event, regardless of the tank size or share refueled at each event (i.e., the time it takes to get to and from the pump). The variable component is the ratio of the average number of gallons refueled for each event – the product of the tank size and share refueled – and the rate at which gallons flow from the pump. This is shown in Equation 6-4.

Equation 6-4: Calculating the Time of Refueling Events

$$Event\ Time_{Veh}=Fixed\ _{Veh}+\frac{Tank_{Veh}*Share_{Veh}}{Rate}$$

The value of time is taken from DOT guidance on travel time savings, as described in Chapter 6.1.4.1. The fixed time component, share refueled, and rate of flow are calculated from survey data gathered as part of our 2010-2011 National Automotive Sampling System's Tire Pressure Monitoring System (TPMS) study.[879] Finally, the vehicle fuel tank sizes are taken from manufacturer specs for the reference fleet, and historical averages are calculated from popular models for the existing vehicle fleet, as described later in this subchapter and in Table 6-8 through Table 6-10.

We estimated the amount of saved refueling time using survey data gathered as part of the aforementioned TPMS study. In this nationwide study, researchers gathered information on the total amount of time spent pumping and paying for fuel. From a separate sample (also part of the TPMS study), researchers conducted interviews at the pump to gauge the distances that drivers travel in transit to and from fueling stations, how long that transit takes, and how many gallons of fuel are purchased. The TPMS survey includes light-duty PVs, utility vehicles, van-based light trucks, and light convenience trucks. Heavy-duty pickups and vans were excluded from the survey. For the following calculations, NHTSA assumes the refueling trip characteristics for heavy-duty pickups and vans is similar to light-duty pickups.

We focused on the interview-based responses in which respondents indicated the primary reason for the refueling trip was a low reading on the gas gauge. These drivers experience a cost due to added mileage driven to detour to a filling station, as well as added time to refuel and complete the transaction at the filling station. Drivers who refuel on a regular schedule or during incidental stops for other reasons (e.g., using restrooms or buying snacks) do not experience the cost associated with detouring in order to locate a station or paying for the transaction, because the frequency of refueling for these reasons is unlikely to be affected by fuel economy improvements. This restriction was imposed to exclude distortionary effects of those who refuel on a fixed (e.g., weekly) schedule and may be unlikely to alter refueling patterns as a result of increased driving range. The relevant TPMS survey data on average refueling trip characteristics are presented below in Table 6-7.

Table 6-7: Average Refueling Trip Characteristics for Passenger Cars and Light Trucks

	Gallons of Fuel Purchased	Round-Trip Distance to/from Fueling Station (miles)	Round-Trip Time to/from Fueling Station (minutes)	Time to Fill and Pay (minutes)	Total Time (minutes)
Passenger Cars (PCs)	10	0.97	2.28	4.1	6.38

[879] NHSTA. Docket for Peer Review of NHTSA/NASS Tire Pressure Monitoring System. Available at https://www.regulations.gov/docket?D=NHTSA-2012-0001. (Accessed: Feb. 14, 2024).

Light-Duty Trucks (LTs)	13	1.08	2.53	4.3	6.83

From the data, we assume that all of the round-trip time necessary to travel to and from the fueling station is a part of the fixed time component of each refueling event. Some portion of the time to fill and pay is also a part of the fixed time component. Given the information in Table 6-7, we assume that each refueling event has a fixed time component of 3.48 minutes. It takes passenger cars, for example, 2.28 minutes travel round trip to/from a fueling station and roughly 1.2 minutes to select and pay for fuel, remove/recap fuel tank, remove/replace fuel nozzle, etc. The time to fill the fuel tank is the variable time component – about 2.9 minutes for passenger cars. Total time to refuel for a passenger car takes 6.38 total minutes (2.28 + 1.2 + 2.9).

To calculate the variable time component, the agency estimates how much time is spent during a refueling event just pumping gas. Cars have an average tank size of about 15 gallons, SUVs/vans of about 18 gallons, and light-duty and heavy-duty pickups of about 27 gallons (see Table 6-8 through Table 6-10). For simplicity of this calculation, the agency assumes that the average passenger car has a tank of 15 gallons and the average light truck — which includes SUVs for this calculation — has a tank of 20 gallons; there are more SUVs/vans than pickups in the light truck fleet and HDPUV fleet. From these assumptions, we calculate that the average refueling event fills approximately 65 percent of the fuel tank — as derived from the TPMS study — for passenger cars, light trucks, and heavy-duty pickups and vans). This value is used as an input in the CAFE Model for both styles (cars and SUVs/vans/pickups). Finally, the rate of the pump flow can be calculated either as the total gallons pumped over the assumed variable time component (approximately 3 minutes) or as the difference in the average number of gallons filled between light trucks and passenger cars over the difference in the time to fill and pay between the two classes. The first methodology implies a rate between 3 and 4 gallons per minute. Although the second methodology implies a rate of 15 gallons per minute, there is a legal restriction on the flow of gasoline from pumps of 10 gallons per minute.[880] Thus, we assume the rate of gasoline pumps range between 4 and 10 gallons per minute and use 7.5 gallons per minute — a value slightly above the midpoint of that range — as the average flow rate in the CAFE Model for light-duty vehicles and heavy-duty pickups and vans.

The calculations described above are repeated for each future calendar year in the analysis. As a vehicle ages, the refueling benefit attributable to it decreases — as older vehicles are typically driven less, which means less fuel consumption and fewer refueling events[881] — until the vehicle is scrapped.

More stringent regulatory alternatives cause fleet turnover to slow, and as a result, older and less efficient vehicles are relied upon to drive additional miles. This shift of VMT from newer to older vehicles diminishes a portion of the refueling benefit accrued under stricter standards. The CAFE Model calculates the aggregate refueling costs for all vehicles — new and the existing fleet — and calculates the refueling benefit associated with more stringent standards as the difference in fleet-wide absolute refueling costs relative to the baseline.

The CAFE Model tracks the legacy fleet of light-duty vehicles by body style and vintage, using average measures for fuel economy. Estimating refueling costs for these vehicles requires measures of average fuel tank sizes by body style and vintage. We used publicly available data on fuel tank sizes of 17 high-volume nameplates to derive estimates of average fuel tank size over time.[882] The tank sizes are averaged by body style, and these historical values are used as estimates of the average by body style and vintage. The vehicles included, their fuel tank sizes, and the averages are reported in Table 6-8 through Table 6-10 for cars, vans/SUVs, and pickups, respectively. The averages are used to represent the fuel tank sizes by vintage and vehicle body style. We used the fuel tank sizes from Table 6-8 to Table 6-10 to determine the number of refueling events and time spent refueling to compute refueling costs using the methodology described above.

[880]Code of Federal Regulations. 40 CFR 1090.1550 (b). Requirements for gasoline dispensing nozzles used with motor vehicles. Available at: https://www.ecfr.gov/current/title-40/section-1090.1550 (Accessed: May 9, 2024).
[881] See Chapter 4.3.2.
[882] Fuel tank capacity data can be found at https://www.edmunds.com. Select the “Car Reviews” header to search specific vehicle make, model, and year features.

Table 6-8: Fuel Tank Size of High-Volume Car Models and Averages by Vintage (gallons)

Model Year	Honda Civic	Honda Accord	Toyota Corolla	Toyota Camry	Ford Mustang	Chevy Corvette	Car Average
1975	10.0		13.2		12.4	17.0	13.2
1976	10.0	13.2	13.2		12.4	17.0	13.2
1977	10.0	13.2	13.2		12.4	17.0	13.2
1978	10.6	13.2	13.2		12.4	24.0	14.7
1979	10.6	13.2	13.2		12.5	24.0	14.7
1980	10.8	13.2	13.2	16.1	12.5	24.0	15.0
1981	10.8	13.2	13.2	16.1	12.5	24.0	15.0
1982	12.2	15.9	13.2	16.1	15.4	24.0	16.1
1983	12.2	15.9	13.2	14.5	15.4	24.0	15.9
1984	12.2	15.9	13.2	14.5	15.4	20.0	15.2
1985	12.2	15.9	13.2	14.5	15.4	20.0	15.2
1986	12.2	15.9	13.2	14.5	15.4	20.0	15.2
1987	12.2	15.9	13.2	15.9	15.4	20.0	15.4
1988	11.9	15.9	13.2	15.9	15.4	20.0	15.4
1989	11.9	15.9	13.2	15.9	15.4	20.0	15.4
1990	11.9	16.9	13.2	15.9	15.4	20.0	15.6
1991	11.9	16.9	13.2	15.9	15.4	20.0	15.6
1992	11.9	16.9	13.2	18.5	15.4	20.0	16.0
1993	11.9	16.9	13.2	18.5	15.4	20.0	16.0
1994	11.9	16.9	13.2	18.5	15.4	20.0	16.0
1995	11.9	16.9	13.2	18.5	15.4	20.0	16.0
1996	11.9	16.9	13.2	18.5	15.4	20.0	16.0
1997	11.9	16.9	13.2	18.5	15.4	19.1	15.8
1998	11.9	17.2	13.2	18.5	15.7	19.1	15.9
1999	11.9	17.2	13.2	18.5	15.7	19.1	15.9
2000	11.9	17.2	13.2	18.5	15.7	18.5	15.8
2001	13.2	17.2	13.2	18.5	15.7	18.5	16.1
2002	13.2	17.2	13.2	18.5	15.7	18.5	16.1
2003	13.2	17.2	13.2	18.5	15.7	18.5	16.1
2004	13.2	17.2	13.2	18.5	15.7	18.0	16.0
2005	13.2	17.2	13.2	18.5	16.6	18.0	16.1
2006	13.2	17.2	13.2	18.5	16.6	18.0	16.1
2007	13.2	17.2	13.2	18.5	16.6	18.0	16.1
2008	13.2	18.5	13.2	18.5	16.6	18.0	16.3
2009	13.2	18.5	13.2	18.5	16.6	18.0	16.3
2010	13.2	18.5	13.2	18.5	16.0	18.0	16.2

2011	13.2	18.5	13.2	18.5	16.0	18.0	16.2
2012	13.2	18.5	13.2	17.0	16.0	18.0	16.0
2013	13.2	17.2	13.2	17.0	16.0	18.0	15.8
2014	13.2	17.2	13.2	17.0	16.0	18.5	15.9
2015	13.2	17.2	13.2	17.0	16.0	18.5	15.9
2016	12.4	17.2	13.2	17.0	16.0	18.5	15.7
2017	12.4	17.2	13.2	17.0	16.0	18.5	15.7
2018	12.4	14.8	13.2	16.0	16.0	18.5	15.2
2019	12.4	14.8	13.2	16.0	16.0	18.5	15.2
2020	12.4	14.8	13.2	15.8	16.0	18.5	15.1
2021	12.4	14.8	13.2	15.8	16.0	18.5	15.1

Table 6-9: Fuel Tank Size of High-Volume Van/SUV Models and Averages by Vintage (gallons)

Model Year	Jeep Wrangler	Ford Explorer	Jeep Grand Cherokee	Chevy Blazer	Ford Escape	Honda CR-V	Toyota Rav4	SUVs Average
1975				31.0				31.0
1976				31.0				31.0
1977				31.0				31.0
1978				31.0				31.0
1979				31.0				31.0
1980				31.0				31.0
1981				31.0				31.0
1982				31.0				31.0
1983				31.0				31.0
1984				31.0				31.0
1985				31.0				31.0
1986				31.0				31.0
1987	20.0			31.0				25.5
1988	20.0			31.0				25.5
1989	20.0			31.0				25.5
1990	20.0			31.0				25.5
1991	20.0	19.3		30.0				23.1
1992	20.0	19.3		30.0				23.1
1993	20.0	19.3	23.0	30.0				23.1
1994	20.0	19.3	23.0	30.0			15.3	21.5
1995	20.0	19.3	23.0	20.0			15.3	19.5
1996	20.0	21.0	23.0	19.0			15.3	19.7
1997	19.0	21.0	23.0	19.0		15.3	15.3	18.8
1998	19.0	21.0	23.0	19.0		15.3	15.3	18.8

1999	19.0	21.0	20.5	19.0		15.3	15.3	18.4
2000	19.0	21.0	20.5	19.0		15.3	15.3	18.4
2001	19.0	21.0	20.5	19.0	16.0	15.3	14.7	17.9
2002	19.0	22.5	20.5	19.0	16.0	15.3	14.7	18.1
2003	19.0	22.5	20.5	19.0	16.0	15.3	14.7	18.1
2004	19.0	22.5	20.5	19.0	16.0	15.3	14.8	18.2
2005	19.0	22.5	20.5	19.0	16.5	15.3	14.8	18.2
2006	19.0	22.5	20.5	22.0	16.5	15.3	15.9	18.8
2007	19.0	22.5	21.1	22.0	16.5	15.3	15.9	18.9
2008	22.5	22.5	21.1	22.0	16.5	15.3	15.9	19.4
2009	22.5	22.5	21.1	22.0	16.5	15.3	15.9	19.4
2010	22.5	22.5	21.1		16.5	15.3	15.9	19.0
2011	22.5	18.6	24.6		17.5	15.3	15.9	19.1
2012	22.5	18.6	24.6		17.5	15.3	15.9	19.1
2013	22.5	18.6	24.6		15.1	15.3	15.9	18.7
2014	22.5	18.6	24.6		15.1	15.3	15.9	18.7
2015	22.5	18.6	24.6		15.1	15.3	15.9	18.7
2016	22.5	18.6	24.6		15.1	15.3	15.9	18.7
2017	22.5	18.6	24.6		15.7	14.0	15.9	18.6
2018	21.5	18.6	24.6		15.7	14.0	15.9	18.4
2019	21.5	18.6	24.6	19.4	15.7	14.0	14.5	18.3
2020	21.5	17.9	24.6	19.4	14.7	14.0	14.5	18.1
2021	21.5	17.9	24.6	19.4	15.7	14.0	14.5	18.2

Table 6-10: Fuel Tank Size of High-Volume Pickup Truck Models and Averages by Vintage (gallons)

Model Year	Ford F150	Dodge Ram	Chevy Silverado	Ford Ranger	Pickups Average
1975	39.2				39.2
1976	39.2				39.2
1977	39.2				39.2
1978	39.2				39.2
1979	39.2				39.2
1980	37.5				37.5
1981	37.5	26.0			31.8
1982	37.5	26.0			31.8
1983	37.5	26.0		19.0	27.5
1984	37.5	26.0		19.0	27.5
1985	37.5	26.0		19.0	27.5
1986	37.5	26.0		19.0	27.5

1987	37.5	26.0		19.0	27.5
1988	37.5	26.0		19.0	27.5
1989	37.5	26.0		19.0	27.5
1990	37.5	26.0		19.0	27.5
1991	37.5	26.0		19.0	27.5
1992	37.5	26.0		19.0	27.5
1993	37.5	30.5		18.8	28.9
1994	37.5	30.5		18.8	28.9
1995	37.5	30.5		18.8	28.9
1996	37.5	30.5		18.8	28.9
1997	30.0	30.5		18.8	26.4
1998	30.0	30.5		18.5	26.3
1999	30.0	30.5	30.0	18.5	27.3
2000	30.0	30.5	30.0	18.5	27.3
2001	30.0	30.5	30.0	18.5	27.3
2002	30.0	30.5	30.0	18.5	27.3
2003	30.0	30.5	30.0	18.5	27.3
2004	30.0	30.5	30.0	18.5	27.3
2005	30.0	30.5	30.0	18.5	27.3
2006	30.0	30.5	30.0	18.5	27.3
2007	30.0	30.5	30.0	18.5	27.3
2008	30.0	30.5	30.0	18.5	27.3
2009	26.0	29.0	30.0	18.5	25.9
2010	26.0	29.0	30.0	18.3	25.8
2011	26.0	29.0	30.0	18.3	25.8
2012	26.0	29.0	30.0		28.3
2013	26.0	29.0	30.0		28.3
2014	26.0	29.0	30.0		28.3
2015	23.0	29.0	30.0		27.3
2016	23.0	29.0	30.0		27.3
2017	23.0	29.0	30.0		27.3
2018	23.0	29.0	30.0		27.3
2019	23.0	29.0	30.0	18.0	25.0
2020	23.0	29.0	30.0	18.0	25.0
2021	23.0	29.0	30.0	18.0	

After calculating the aggregate value for each regulatory alternative using the methodology and inputs described above for both the new and legacy fleets, the model calculates the incremental value relative to the baseline as the refueling cost or benefit for that regulatory alternative. More efficient vehicles have to be refueled less often and refueling costs per vehicle decline.

6.1.4.3. Including Electric Vehicle Recharging

In addition to including the refueling costs associated with the “legacy fleet,” the CAFE Model also adds the cost to recharge electric vehicles to the total refueling costs. Even though electrified pathways are not available as a compliance pathway to meet the finalized standards in our standard setting runs, accounting for the cost of recharging electric vehicles becomes increasingly relevant as they become more prevalent.[883] In order to do so, it is important to first understand how many electric vehicle charging events will require the driver to wait and the duration of the waiting period – which is dependent on the range of the electric vehicle and the length of the trip[884]. For trips shorter than the vehicle’s range, the driver can recharge the vehicle at times that will not require them to be actively waiting, and there would be no time cost related to recharging. Only for trips where the vehicle is driven for more miles than the vehicle’s range will the driver have to stop mid-trip, a time that is assumed to be inconvenient, to recharge the vehicle at least enough to reach the intended destination.

NHTSA used trip data from the National Household Transportation Survey (NHTS) to estimate the frequency and expected length of trips that exceed the range of the electric vehicle technologies in the simulation (200 and 350-mile ranges – which were extrapolated for longer battery ranges). NHTS collects data on individual trips by mode of transportation from a representative random sample of U.S. households. A trip is defined by the starting and ending point for any personal travel, so that vehicle trips will capture any time a car is driven. The survey includes identification numbers for households, individuals, and vehicles, as well as mode of transportation (including the body style of the vehicle for vehicle trips), and the date of the trip. Although some trips made in the same day may allow for convenient charging in between trips, we assume that travel in the same day exceeding the range will involve the driver waiting for the vehicle to charge. Thus, the total number of miles driven by the same vehicle in a single day is summed, and we assume that charging stations are not conveniently available to the driver in between.

From the final body style datasets (which excludes taxis and rental cars), we calculated two measures that allow for the construction of the value of recharging time. First, the expected distance between trips that exceed the range of 200-mile and 350-mile BEVs was calculated. This is calculated as the quotient of the sum of total miles driven by each individual body style and the total number of trips exceeding the range, as shown in Equation 6-5.[885]

Equation 6-5: Calculation of En Route Charge Frequency

$$\textit{Charge Frequency}_{\textit{Style, Range}} = \frac{\sum_{\textit{Trip} \in \textit{Style}} \textit{Trip Length}}{\sum_{\textit{Trip} \in \textit{Style}} [\textit{Trip Length} > \textit{Range}]}$$

This calculates the expected frequency of enroute recharging events, or the number of miles traveled per inconvenient recharging event. It is used later to calculate the total expected time to recharge a vehicle.

The second measure needed to calculate the total expected recharging time is the expected share of miles driven that will be fueled by a charge in the middle of a trip (causing the driver to wait and lose the value of time). To calculate this measure, we sum the difference of the trip length and range, conditional on the trip length exceeding the range for each body style. This figure is then divided by the sum of the length of all trips for that body style, as in Equation 6-6.

Equation 6-6: Share of Battery Electric Range Charged

$$\textit{Share Charged}_{\textit{Style, Range}} = \frac{\sum_{\textit{Trip} \in \textit{Style}} ([\textit{Trip Length} > \textit{Range}] * (\textit{Trip Length} - \textit{Range}))}{\sum_{\textit{Trip} \in \textit{Style}} \textit{Trip Length}}$$

[883] Since the size of the BEV population does not increase to meet the finalized standards in our standard setting runs, the costs to recharge do not influence the cost-benefit analysis.
[884] While the range of EVs is dependent on a number of factors, such as driver habits, geography, and weather, NHTSA took a conservative approach and assumed a best-case scenario.
[885] The denominator counts the number of necessary recharging events by body style. It is not a measurement of VMT.

The calculated frequency of inconvenient charging events and share of miles driven that require the driver to wait for BEVs with varying range capabilities are presented in Table 6-11, below. As the table shows, cars are expected to require less frequent inconvenient charges and a smaller share of miles driven will require the driver to charge the vehicle in the middle of a trip. Pickups and vans/SUVs have fairly similar measures, with vans and SUVs requiring slightly more inconvenient charging than pickups — with the heavy-duty pickup and van fleet being the least convenient to charge.

Table 6-11: Electric Vehicle Recharging Thresholds by Body Style and Range[886, 887]

Body Style	Cars	Vans/SUVs	Pickups	HDPUVs
Miles until mid-trip charging event, BEV1	2,000	1,500	1,600	1,200
Miles until mid-trip charging event, BEV2	3,600	2,500	2,700	1,700
Miles until mid-trip charging event, BEV3	5,200	3,500	3,800	N/A
Miles until mid-trip charging event, BEV4	10,400	7,000	7,600	N/A
Share of miles charged mid-trip, BEV1	6.00%	9.00%	8.00%	12.50%
Share of miles charged mid-trip, BEV2	4.50%	6.50%	6.00%	7.00%
Share of miles charged mid-trip, BEV3	3.00%	4.00%	4.00%	N/A
Share of miles charged mid-trip, BEV4	1.50%	2.00%	2.00%	N/A
Charge rate (miles/hour), BEV1	67	67	67	67
Charge rate (miles/hour), BEV2	100	100	100	100
Charge rate (miles/hour), BEV3	100	100	100	N/A
Charge rate (miles/hour), BEV4	100	100	100	N/A

The measures presented in Table 6-11 can be used to calculate the expected time drivers of electric vehicles of a given body style and range will spend recharging at a time that will require them to wait. First, NHTSA calculates the expected number of refueling events for a vehicle of a given style and range in a given calendar year. This is shown in Equation 6-7 as the expected miles driven by a vehicle in a given calendar year divided by the charge frequency of a vehicle of that style and range from Table 6-11.[888]

[886] Ranges for light-duty BEVs are as follows: $BEV1_{LD} \leq 225$ miles; 225 miles < $BEV2_{LD} \leq 275$ miles; 275 miles < $BEV3_{LD} \leq 350$ miles; 350 miles < $BEV3_{LD}$. BEV ranges for HDPUVs differ from the light-duty fleet, and vary depending on whether the vehicle is a van or pickup; the ranges are as follows: $BEV1_{HDPUV\_VANS} \leq 150$ miles and $BEV1_{HDPUV\_TRUCKS} \leq 200$ miles; 150 miles < $BEV2_{HDPUV\_VANS} \leq 250$ miles; 200 miles < $BEV2_{HDPUV\_TRUCKS} \leq 300$ miles.
[887] Note that these charge rates are low relative to what is available in the market now, but it reflects the avaiability of inftrasructure in the US at this time.
[888] Note that $\sum_{Trip\ \epsilon\ Style} Trip\ Length$ and $Miles_{CY,\ Veh}$ are different values. $Miles_{CY,\ Veh}$ is the estimated amount of VMT predicted by VMT while $\sum_{Trip\ \epsilon\ Style} Trip\ Length$ is the sum of trips observed by the NHTS study.

Equation 6-7: Calculation of Recharge Events

$$Recharge\ Events_{CY,\ Veh\ \epsilon\ (Style\ \cup\ Range)} = \frac{Miles_{CY,\ Veh}}{Charge\ Frequency_{Style,\ Range)}}$$

We next calculate the number of miles charged for a vehicle of a given style and range in a specific calendar year. This is the product of the number of miles driven by the vehicle and the share of miles driven that require an inconvenient charge for a vehicle of that style and range (from Table 6-11) as presented in Equation 6-8.

Equation 6-8: Calculation of Miles Charged

$$Miles\ Charged_{CY,\ Veh\ \epsilon\ (Style\ \cup\ Range)} = Miles_{CY,\ Veh} * Share\ Charged_{Style,\ Range}$$

Finally, we calculate the expected time that a driver of an electric vehicle (of a given style and range) will spend waiting for the vehicle to charge. This is the product of the fixed amount of time it takes to get to the charging station and the number of recharging events plus the quotient of the expected miles that will require inconvenient charging over an input assumption of the rate of which a vehicle of that style and range can be charged in a given calendar year (expressed in units of miles charged per hour). The fixed amount of time it takes to get to a charging station is set equal to the average time it takes for an ICE vehicle to get to a gas station for a refueling event, as discussed above[889]. This is shown in Equation 6-9.

Equation 6-9: Calculation of Charging Time

$$Charge\ Time_{CY,\ Veh\ \epsilon\ (Style\ \cup\ Range)} = (Fixed_{\ Veh} * Recharge\ Events_{CY,\ Veh}) + \frac{Miles\ Charged_{CY,\ Veh}}{Charge\ Rate_{CY,\ Veh}}$$ [890]

The expected time that a driver will wait for their vehicle to charge can then be multiplied by the value of time estimate, as is done with gasoline, diesel, and E85 vehicles (see descriptions above in Chapter 6.1.4.1 and Chapter 6.1.4.2 of the current approach to accounting for refueling time costs).

Plug-in hybrids are treated somewhat differently in the modeling. Presumably, plug-in hybrids that are taken on a trip that exceed their electric range will be driven on gasoline and the driver will recharge the battery at a time that is convenient. For this reason, the electric portion of travel should be excluded from the refueling time calculation. The gasoline portion of travel is treated the same as other gasoline vehicles so that when the tank reaches some threshold, the vehicles are assumed to be refueled with the same fixed event time and the same rate of refueling flow.

6.1.5. Benefits of Additional Mobility

Increased travel provides benefits that reflect the value to drivers and their passengers of access to added—or more desirable—economic, social, and recreational opportunities. Under each regulatory alternative considered in this analysis, the fuel CPM of driving would decrease as a consequence of the higher fuel economy and efficiency levels it required. This will increase the number of miles that buyers drive through the well-documented fuel economy rebound effect.

The fact that drivers and their passengers elect to make more frequent or longer trips to gain access to additional opportunities when the cost of driving declines demonstrates that the benefits, they gain by doing so must exceed the costs they incur. At a minimum, these benefits must be large enough to offset the cost of the fuel consumed in traveling the additional miles, or they would not have been driven. Because the cost of fuel consumed by this additional rebound-effect driving has already been accounted for in the estimated fuel expenditures for each regulatory alternative, it is also necessary to account for the benefits associated with

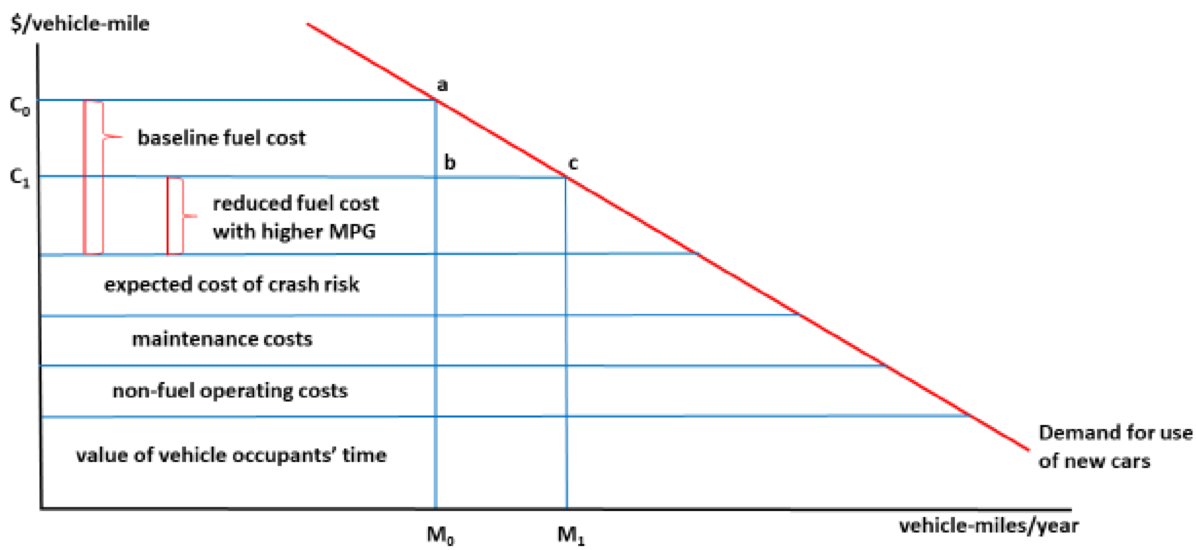
[889] Given the current state charging infrastructure, this is likely a conservative estimate. Gas stations vastly outnumber publicly available recharging stations and are often in more convenient locations.

the additional miles traveled.[891] The amount by which the benefits of this additional travel *exceed* its economic costs measures the net benefits drivers and their passengers experience, usually referred to as increased consumer surplus.

The structure of these additional benefits is described by Figure 6-2, below. In the figure, the triangle abc is the consumer surplus associated with the additional travel, and the area of the rectangle immediately below triangle abc represents the cost of the fuel consumed by driving those additional miles.[892] The rectangle immediately below that corresponding to increased fuel costs represents the internalized benefit of increased exposure to vehicular crashes. While we assume that drivers consider the added safety risks they assume when they undertake additional trips, we assume that they do not *completely* internalize any risks they impose on other drivers when they travel more. So, unlike the corresponding benefit associated with the additional fuel cost of rebound travel, which fully offsets the increased cost, the offsetting benefit of safety risk is assumed to offset only 90 percent of the (social) cost of increasing safety risk, as discussed further in Chapter 7.5.

While Figure 6-2 also shows driving costs related to maintenance, non-fuel operating costs, and the value of occupants' travel time, increases in these other cost elements due to the added rebound-effect driving are not accounted for directly in the analysis. Because we do not estimate these additional costs of increased driving, there is no need to separately account for an offsetting benefit (as we do with other components of the mobility costs related to added rebound-effect travel).

Figure 6-2: The Benefit of Additional Mobility



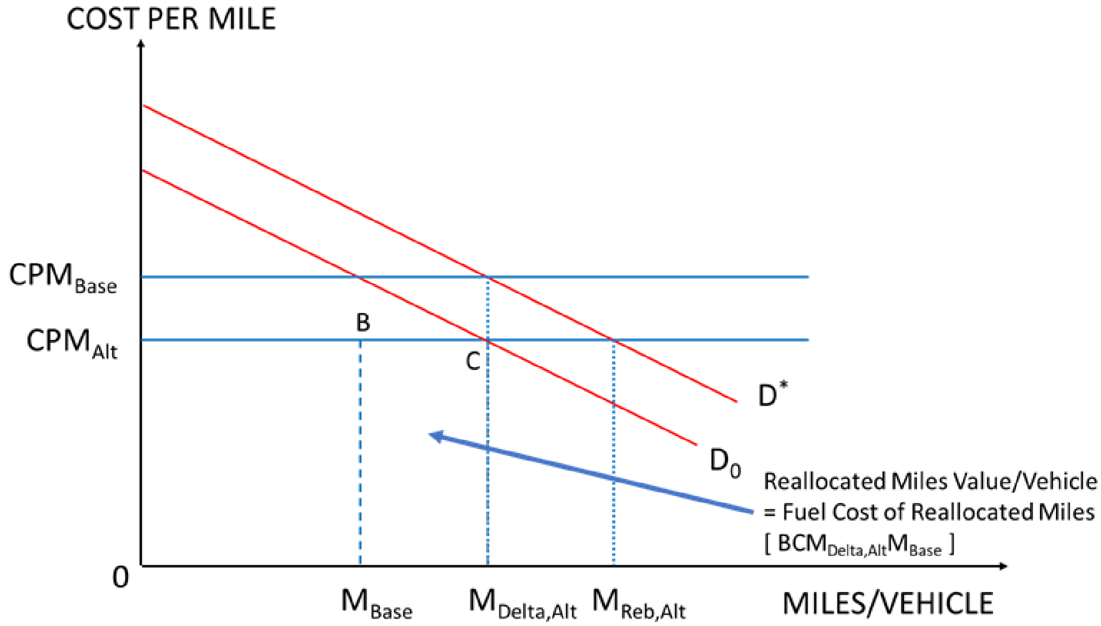
In general, CAFE and fuel efficiency standards change the quantities of new vehicles sold in future years. When future vehicle sales differ from the baseline, the CAFE Model adjusts miles traveled per vehicle-by-vehicle type, model year and age to ensure that total miles traveled, prior to adjustments for the rebound effect, are the same across alternatives (see Chapter 4.3.2). When new vehicle sales decrease relative to the baseline, miles per vehicle increase because the same number of miles per year is assumed to be driven using fewer vehicles. The reallocation of some VMT to existing vehicles implies that consumers are willing to pay their higher fuel costs for the additional travel, which again implies a corresponding per vehicle travel benefit at least as great as these added fuel costs. However, estimating the corresponding benefit complicates the analysis somewhat.

[891] The benefits from additional travel must also offset the economic value of their (and their passengers') travel time, other vehicle operating costs, and the economic cost of safety risks due to the increase in exposure that occurs with additional travel.
[892] The CAFE Model tracks mileage accrual for new vehicles atomically, at the row level, and is thus able to separate the fuel cost of rebound travel on a per-vehicle basis. It then aggregates all of those individual benefits to construct the aggregate estimate of increased mobility.

Figure 6-3 illustrates the consumer benefit in question. In the figure, D_0 is the per-vehicle travel demand curve in the baseline. Reallocating a quantity of miles equal to $M_{Delta,Alt} – M_{Base}$ to each vehicle in effect shifts the demand curve outward to D^*. This increases fuel expenditures by an amount equal to the reallocated miles times the fuel CPM under the alternative, i.e., by the dollar value of rectangle $(M_{Delta,Alt} – M_{Base})*CPM_{Alt}$. The increase in vehicle miles due to the rebound effect of lower fuel CPM ($CPM_{Alt} < CPM_{Base}$) also increases fuel costs, by the dollar value of the rectangle with area equal to $(M_{Reb,Alt} – M_{Delta,Alt})*CPM_{Alt}$.

Both sources of the increase in fuel costs are included when the total fuel costs by vehicle type, model year and age are divided by the corresponding number of vehicles. While the benefit to the consumer of the additional driving induced by the rebound effect is accounted for using the method described previously, it is also important to include the per vehicle benefit from driving these reallocated miles, since the fuel costs for driving them are already included in the calculated fuel savings.

Figure 6-3: Per Vehicle Change in Vehicle Travel as a Function of Cost-per-Mile



Because total non-rebound VMT does not change from the baseline to the alternatives, there is no change in consumers' surplus due to the reallocation of miles in the alternative cases. For this reason, we calculate only the portion of the value of reallocated miles that is equivalent to the fuel cost per vehicle associated with those miles in order to offset the increase in fuel costs per vehicle caused by the reallocated miles.[893] The mobility value of reallocated miles is calculated as, (Reallocated VMT Alternative - Reallocated VMT baseline)(Alternative Cost per Mile), or in Figure 6-3, $(M_{Delta,Alt} - M_{Base})CPM_{Alt}$.[894] A detailed explanation of the method of calculation is available in the CAFE Model Documentation, Section S8.8.2.

In contrast to the societal cost-benefit analysis, calculation of average costs and benefits to consumers is done on a per-vehicle basis and is intended to describe how alternative standards affect the costs and benefits of buying and owning individual vehicles when viewed from the consumers' perspective. The adjustment to account for re-allocated miles is specific to the calculation of the per vehicle value of mobility and does not apply to the overall cost-benefit analysis.

[893] By reallocating every mile that would have been traveled by the vehicles not sold (in the case of a reduction in new vehicle sales), we implicitly assume that consumers are indifferent between travel in the new vehicles versus the existing vehicles to which the travel is reallocated. In general, some change in total travel would be expected due to the differences in the attributes of new and existing vehicles. However, by reallocating every mile we implicitly assume there is no change in consumers' welfare due to the reallocation. For this reason, we do not estimate a per-vehicle change in consumers' surplus associated with the reallocated miles beyond the value that effectively cancels the increase in fuel cost per vehicle.
[894] The VMT reallocated in the baseline ensures that baseline VMT is consistent with the forecasts of the FHWA VMT model by adjusting the VMT per vehicle type and age of the reference year fleet (see Chapters 4.3.1 and 4.3.2 above).

6.2. External Benefits and Costs

In addition to the benefits and costs that establishing higher standards creates for manufacturers and buyers of new cars and trucks, NHTSA's analysis evaluates several impacts its action is likely to have on the general public, the U.S. economy, and even global economic activity. The agency refers to these indirect impacts as "external" costs and benefits from establishing more stringent standards, because they extend well beyond the private businesses and households that experience the more direct effects of raising CAFE and fuel efficiency standards.

The most significant external benefit from reducing fuel consumption is lower GHG emissions and the consequent reduction in the expected economic damages caused by changes in the future global climate those emission would have caused. Chapter 5.2 and Chapter 5.3 explain how the agency estimates the reductions in emissions of GHGs that are likely to result from establishing stricter standards, and Chapter 6.2.1 explains how the agency values the associated reduction in future climate-related economic damages, which are likely to extend to nations and regions well outside U.S. borders.

As Chapter 5 discussed, reductions in emissions of criteria air pollutants and the health damages they cause for the U.S. population are also likely to result from raising standards. Chapter 6.2.2 below explains how NHTSA estimates the economic value of changes in health outcomes. Finally, Chapter 6.2.3 discusses how U.S. consumption and imports of petroleum can generate economic externalities that impose potential costs beyond those to consumers of petroleum products and describes how reducing gasoline consumption can limit the costs of these externalities, thus generating additional external benefits.

At the same time, raising CAFE and fuel efficiency standards is likely to impose some costs that extend beyond private impacts on producers and buyers of new cars, light trucks, and HDPUVs, and beyond the related economic transfers (such as sales taxes on new vehicle purchases) discussed above. As Chapter 4.3.5 describes, improving fuel economy and efficiency is likely to increase the number of miles that vehicles are driven via the well-documented fuel economy rebound effect. This additional driving will contribute to increased traffic congestion and road noise, the impacts of which will extend to road users other than those traveling in new vehicles, as well as to residents of areas surrounding streets and highways. Chapter 6.2.3 explains how NHTSA estimates of the costs of these congestion and noise externalities.

Some fraction of the safety risks that buyers of new vehicles impose when they drive additional miles is likely to be borne by occupants of other vehicles using the same roads, as well as perhaps by pedestrians and bystanders. Chapter 7.5 describes how the agency estimates this "external" component of safety risks from additional rebound-effect driving, and how NHTSA calculates the fraction of costs from fatalities, injuries, and property damage to vehicles that are borne by road users other than drivers and passengers of new vehicles.

Finally, reducing fuel consumption by raising standards will lower fuel tax revenue collected by government agencies. Taxes are considered a transfer in the analysis, so while we include the lost tax revenue as a societal cost in our accounting, consumers experience an exactly offsetting savings in fuel tax payments, which has already been included in our estimates of fuel cost savings. The net effect is thus to treat the reduction in fuel tax revenue as a transfer from government agencies to new vehicle buyers that has no net effect on economic welfare.

6.2.1. Social Costs of Greenhouse Gas Emissions

The combustion of petroleum-based fuels that power cars, light trucks, and HDPUVs generates emissions of various greenhouse gases (GHGs), which contribute to changes in the global climate which in turn cause economic damages. The processes of extracting and transporting crude petroleum, refining it to produce transportation fuels, and distributing fuel for retail sale each generate additional GHG emissions ("upstream" emissions), as does generating electricity that is used to power PHEVs, BEVs, and FCEVs. By reducing the volume of petroleum-based fuel produced and consumed by cars, light trucks, and HDPUVs, the final standards will reduce both direct GHG emissions from fuel consumption by vehicles and upstream emissions from supplying petroleum-based fuels.

NHTSA's analysis quantifies resulting changes in emissions of three important GHGs: carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). For an extensive discussion of the definitions, sources, and impacts of these GHGs, see Chapter 5 of the Final EIS accompanying the final rule. Chapter 5 of this TSD details how NHTSA estimates changes in GHG emissions expected to result from the different rulemaking alternatives. The agency calculates the monetized climate benefits resulting from anticipated reductions in emissions of each of these three GHGs using estimates of the social costs of greenhouse gases (SC-GHG) values reported in a recent report from EPA (hereinafter referred to as the "2023 EPA SC-GHG Report").[895] In the proposed rule and numerous prior analyses, NHTSA used values reported by the federal Interagency Working Group (IWG) on the SC-GHG.[896] NHTSA has elected to use the updated values in the 2023 EPA SC-GHG Report to reflect the most recent scientific evidence on the cost of climate damages resulting from emission of GHGs.

6.2.1.1. Estimated Social Costs of GHGs

In theory, the SC-GHG captures the value of all climate change impacts (both negative and positive) attributable to changes in GHG emissions, including (but not limited to) changes in net agricultural productivity, human health effects, property damage from increased flood risk and natural disasters, disruption of energy systems, risk of conflict, environmental migration, and the value of ecosystem services. The SC-GHG therefore, reflects the societal value of reducing emissions of the gas in question by one metric ton. The SC-GHG is the theoretically appropriate value to use in conducting benefit-cost analyses of policies that affect GHG emissions. In practice, data and modeling limitations naturally restrain the ability of SC-GHG estimates to include all the important physical, ecological, and economic impacts of climate change, and as a consequence the estimates represent only a partial accounting of climate change impacts and will tend to underestimate the marginal benefits of abatement. The SC-GHG differs by the type of GHG (such as CO_2, CH_4, and N_2O) and by the year in which the emissions change occurs. NHTSA uses SC-GHG estimates (specifically, social cost of carbon (SC-CO_2), social cost of methane (SC-CH_4), and social cost of nitrous oxide (SC-N_2O) estimates) presented in Table A.5.1 of the EPA report inflated to 2021 dollars using the implicit price deflator for U.S. GDP in this analysis.[897]

In the analysis conducted for the proposed rule, NHTSA used the interim SC-GHG estimates recommended by the IWG in February 2021. In 2017, the National Academies reviewed the social cost of carbon dioxide (SC-CO_2) and issued a final report with recommendations for future updates to the values.[898] DOT is a member of the IWG and is participating in the group's ongoing deliberations. The 2023 EPA SC-GHG Report presents a set of SC-GHG estimates that incorporate the National Academies' near-term recommendations and is therefore an improvement on the interim estimates of the IWG. Specifically, the National Academies recommended that the SC-GHG should be developed using a modular approach, where the separate modules address socioeconomic projections, climate science, economic damages, and discounting. The National Academies recommended that the methodology underlying each of the four modules be updated by drawing on the latest research and expertise from the scientific disciplines relevant to that module. This is the approach that EPA has taken in its report, which was also subject to notice and comment and peer review to ensure the quality and integrity of the information it contains.[899] Given that the 2023 EPA SC-GHG Report reflects the most recent scientific evidence and the values it presents are constructed consistent with the

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[895] EPA. 2023. EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances. National Center for Environmental Economics, Office of Policy, Climate Change Division, Office of Air and Radiation. Washington, D.C. Available at: https://www.epa.gov/environmental-economics/scghg. (Accessed: March 22, 2024) (hereinafter, "2023 EPA SC-GHG Report").

[896] Interagency Working Group on Social Cost of Greenhouse Gases, United States Government. 2021. Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide Interim Estimates under Executive Order 13990. White House. 1-48. Available at: https://www.whitehouse.gov/wp-content/uploads/2021/02/TechnicalSupportDocument_SocialCostofCarbonMethaneNitrousOxide.pdf. (Accessed: Feb. 14, 2024).

[897] See p. 154 of 2023 EPA SC-GHG Report.

[898] National Academies of Sciences, Engineering, and Medicine. 2017. Valuing Climate Damages: Updating Estimation of the Social Cost of Carbon Dioxide. *The National Academies Press:* Washington, D.C. Available at: https://nap.nationalacademies.org/catalog/24651/valuing-climate-damages-updating-estimation-of-the-social-cost-of.

[899] See p. 3 of 2023 EPA SC-GHG Report for more details on public notice and comment and peer review. This report as part of EPA's Final Oil and Natural Gas Operations can be found at: https://www.epa.gov/controlling-air-pollution-oil-and-natural-gas-operations/epas-final-rule-oil-and-natural-gas (Accessed: May 20, 2024).

framework recommended by the National Academies, NHTSA believes they represent the best SC-GHGs estimates currently available.[900]

NHTSA acknowledges that there are many impacts of global climate change that are not reflected in EPA's estimates of the SC-GHGs. These include omitted damages that are as-yet difficult to estimate, such as impacts due to changes in variation in temperature and precipitation. Further, the estimates do not adequately capture the risk of "tipping points" where climate change could result in permanent changes in the Earth's climate and ecosystems, such as changes in monsoon patterns. For a more detailed discussion of the impacts that may be omitted or incompletely represented, see section 3.2 of EPA's report.[901]

NHTSA's TSD accompanying its proposed rule emphasized the importance of using SC-GHGs estimates that include damages avoided globally by reducing U.S. GHG emissions – including impacts that accrue both domestically and abroad – and NHTSA continues to emphasize this in this TSD. The IWG concluded that a global analysis is essential for SC-GHG estimates because climate impacts can directly and indirectly affect the welfare of U.S. citizens and residents through complex pathways that spill across national borders. Examples include direct effects on U.S. citizens and assets, investments located abroad, international trade, and tourism, and spillover pathways such as economic and political destabilization and global migration that can lead to adverse impacts on U.S. national security, public health, and humanitarian concerns. Those impacts are more fully captured within global measures of the social cost of greenhouse gases.

In addition, assessing the benefits of U.S. GHG mitigation activities requires consideration of how those actions may affect mitigation activities by other countries, as those international mitigation actions will provide a benefit to U.S. citizens and residents by mitigating climate impacts that affect U.S. citizens and residents. A wide range of scientific and economic experts have emphasized the issue of reciprocity as support for considering global damages of GHG emissions. Using a global estimate of damages in U.S. analyses of regulatory actions allows the U.S. to continue to actively encourage other nations, including emerging major economies, to take significant steps to reduce emissions. The only way to achieve an efficient allocation of resources for emissions reduction on a global basis—and so benefit the U.S. and its citizens—is for all countries to base their policies on global estimates of damages.[902]

The SC-GHG values reported in EPA's report and used in the analysis for this final rule provide a global measure of monetized damages from GHG reductions. EPA's report explains that "The US economy is … inextricably linked to the rest of the world" and that "over 20% of American firms' profits are earned on activities outside of the country." On this basis EPA concludes "Climate Impacts that occur outside U.S. borders will impact the welfare of individuals and the profits of firms that reside in the US because of the connection to the global economy…through international markets, trade, tourism, and other activities."[903] NHTSA agrees with EPA that climate damages to the rest of the world will result in the economic damages that will be felt domestically, and, consistent with its position in the proposed rule and numerous prior regulations, concludes that SC-GHG values that incorporate both domestic and international damages are appropriate for its analyses.

While global estimates of the SC-GHG are the most appropriate values to use for the above stated reasons, new modeling efforts suggest that U.S.-specific damages are very likely higher than previously estimated. For instance, the EPA's Framework for Evaluating Damages and Impacts (FrEDI) is a "reduced complexity model that projects impacts of climate change within the United States through the 21st century" that offers insights on some omitted impacts that are not yet captured in global models. [904] Results from FrEDI suggest that damages due to climate change within the contiguous United States are expected to be substantial. EPA's

[900] For more information about the modular approach, there is a concise summary beginning on page 3-8 of U.S. Environmental Protection Agency. *Regulatory Impact Analysis of the Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review* (hereinafter, "2023 Oil and Gas Rule RIA"). EPA-452/R-23-013, Office of Air Quality Planning and Standards, Health and Environmental Impacts Division, Research Triangle Park, NC, December 2023.

[901] 2023 EPA SC-GHG Report.

[902] For more information about the appropriateness of using global estimates of SCGHGs, *see* discussion p. 3-20 of the Oil and Gas Rule RIA.

[903] See section 1.3, 2023 EPA SC-GHG Report.

[904] EPA. 2021. Technical Documentation on the Framework for Evaluating Damages and Impacts (FrEDI). U.S. Environmental Protection Agency, EPA 430-R-21-004. Summary information at https://www.epa.gov/cira/fredi. (Accessed: May 22, 2024.)

recent tailpipe emissions standards cite a FrEDI-produced partial SC-CO_2 estimate of $41 per metric ton.[905] This U.S.-specific value is comparable to SC-CO_2 estimates NHTSA has used for prior rulemakings and used in sensitivity analyses for this rulemaking.[906] NHTSA notes that the FrEDI estimates include impact categories that are not available for the rest of the world – and also that the FrEDI estimates are missing numerous climate impacts, and are thus underestimates of actual climate damages. The damage models applied to generate EPA's estimates of the global SC-CO_2 estimates used in this Final Rule (the Data-driven Spatial Climate Impact Model (DSCIM) and the Greenhouse Gas Impact Value Estimator (GIVE)), which as noted do not reflect many important climate impacts, provide estimates of climate change impacts physically occurring within the United States of $16-$18 per metric ton for 2030 emissions, but these estimates fail to reflect important climate impact categories (such as most impacts of altered precipitation) and fail to capture the effects on the United States of climate impacts that physically occur in other countries. EPA notes that "[w]hile the FrEDI results help to illustrate how monetized damages physically occurring within the [continental US] increase as more impacts are reflected in the modeling framework, they are still subject to many of the same limitations associated with the DSCIM and GIVE damage modules, including the omission or partial modeling of important damage categories."[907] EPA also notes that the DSCIM and GIVE estimates of climate change impacts physically occurring within the United States are, like FrEDI, "not equivalent to an estimate of the benefits of marginal GHG mitigation accruing to U.S. citizens and residents" in part because they "exclude the myriad of pathways through which global climate impacts directly and indirectly affect the interests of U.S. citizens and residents."[908]

Estimating the SC-GHGs involves projecting emissions, population, economic output, interest rates, and more into the far distant future, which inherently involves a high degree of uncertainty due to the complex interplay of these variables over extended time horizons and the unpredictable nature of future technological, societal, and environmental changes. EPA states that its methodologies "allow for a more holistic treatment of uncertainty" by incorporating a "quantitative consideration of uncertainty in all modules and use a Monte Carlo approach that captures the compounding uncertainties across modules." The extent to which social, political, and economic systems will be able to adapt to changes in the global climate in ways that reduce potential disruptions and damage also introduces uncertainty. Recognizing these many important sources of uncertainty, the IWG and EPA recommend that agencies consider a wide distribution of possible SC-GHG values rather than simply the mean or expected values when conducting regulatory analyses.

To summarize, NHTSA believes that the methodologies deployed in the EPA report reflect the best available scientific approach to estimating SC-GHGs, and that the values presented in the report are the best available estimates. That said, NHTSA notes that there are several modeling limitations highlighted in this section in brief and in the 2023 EPA SC-GHG Report more extensively that suggest that the estimates presented in the report are likely underestimates of the true SC-GHGs.

6.2.1.2. Discount Rates for Climate Related Benefits

A standard function of regulatory analysis is to evaluate tradeoffs between impacts that occur at different points in time. Many Federal regulations involve costly upfront investments that generate future benefits in the form of reductions in health, safety, or environmental damages. To evaluate these tradeoffs, the analysis must account for the "social rate of time preference" – the broadly observed social preference for benefits that occur sooner versus those that occur further in the future.[909] This is accomplished by discounting impacts that occur further in the future more than impacts that occur sooner.

Because GHGs degrade slowly and accumulate in the earth's atmosphere, the economic damages they cause increase as their atmospheric concentration accumulates. Because some GHGs emitted today can

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[905] *See* p. *9-16 of* U.S. Environmental Protection Agency. *Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles Regulatory Impact Analysis*. EPA-420-R-24-004, Assessment and Standards Division, Office of Transportation and Air Quality, March 2024.
[906] For instance, NHTSA's previous final rule used a global SC-CO_2 value of $50 in calendar year 2020. *See* Section 6.2 of National Highway Traffic Safety Administration. *Technical Support Document: Final Rulemaking for Model Years 2024-2026 Light-Duty Vehicle Corporate Average Fuel Economy Standards*. March 2022.
[907] *See* p. 9-16 of U.S. Environmental Protection Agency. *Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles Regulatory Impact Analysis*. EPA-420-R-24-004, Assessment and Standards Division, Office of Transportation and Air Quality, March 2024.
[908] 2023 EPA SC-GHG Report.
[909] This preference is observed in many market transactions, including by savers that expect a return on their investments in stocks, bonds, and other equities; firms that expect positive rates of return on major capital investments; and banks that demand positive interest rates in lending markets.

remain in the atmosphere for hundreds of years, burning fossil fuels today not only imposes uncompensated costs on others around the globe today, but also imposes uncompensated damages on future generations. As OMB Circular A-4 (2023) indicates, "[s]pecial ethical considerations arise when comparing benefits and costs across generations," and future citizens impacted by a regulatory choice "cannot take part in making them, and today's society must act with some consideration of their interest."[910] It adds that uncertainty in the discount rate over long time horizons suggests that certainty-equivalent discount rates will have a lower, or declining, schedule. NHTSA's analysis of the proposed rule used the IWG's values for the SC-GHGs constructed at the constant discount rates of 2.5, 3, and 5 percent (compared to the 2003 iteration of OMB Circular A-4's recommended default discount rates of 3 and 7 percent). As such, NHTSA's analysis was consistent with notion that intergenerational considerations merit lower discount rates for rules such as CAFE with impacts over very long time horizons.

The EPA's discounting module represents an advancement of the work of the IWG in a number of ways. Consistent with the National Academies' recommendation, the discounting module relies on a dynamic discounting approach that more fully captures the role of uncertainty in the discount rate in a manner consistent with the other modules. Specifically, rather than using a constant discount rate, the evolution of the discount rate over time is defined following the latest empirical evidence on consumption interest rate uncertainty and using a framework originally developed by Ramsey (1928) that connects economic growth and interest rates. The Ramsey approach explicitly reflects (1) preferences for utility in one period relative to utility in a later period and (2) the value of additional consumption as income changes. EPA calibrated the key parameters in this Ramsey framework such that (1) the decline in the certainty-equivalent discount rate matches the latest empirical evidence on interest rate uncertainty and (2) the average of the certainty-equivalent discount rate over the first decade matches a near-term consumption rate of interest. Uncertainty in the starting rate is addressed by using three near-term target rates (1.5, 2.0, and 2.5 percent) based on multiple lines of evidence on observed market interest rates.

The resulting dynamic discount rate provides a notable improvement over the constant discount rate framework used for previous SC-GHG estimates. Specifically, it provides internal consistency within the modeling and a more complete accounting of uncertainty consistent with economic theory and the National Academies' recommendation to employ a more structural, Ramsey-like approach to discounting that explicitly recognizes the relationship between economic growth and discounting uncertainty. The EPA's approach is also consistent with the National Academies' recommendation to use three sets of Ramsey parameters that reflect a range of near-term certainty-equivalent discount rates and are consistent with theory and empirical evidence on consumption rate uncertainty. Finally, the value of aversion to risk associated with net damages from GHG emissions is explicitly incorporated into the modeling framework following the economic literature. See the 2023 EPA SC-GHG Report for a more detailed discussion of the entire discounting module and methodology used to value risk aversion in the SC-GHG estimates.

The SC-GHG values in the EPA report represent the present value of the stream of avoided climate damages discounted to the future years when emissions would have occurred. Additional discounting is thus required to bring the future values of the avoided damages NHTSA estimates in this final rule back to their present value as of the analysis's initial year 2022. For this operation, EPA's report suggests using one of two approaches. The first approach is more complicated and involves constructing a schedule of certainty-equivalent discount factors that is consistent with a declining discount rate over the time horizon of the analysis. The second approach, which EPA suggests is appropriate for rules where the stream of future emissions reductions being evaluated is moderate (30 years or less), is to discount from the year of abatement to the present using the corresponding constant near-term target rates of 2.5, 2, and 1.5 percent. NHTSA's calendar year analysis includes fewer than 30 years of impacts, and the majority of impacts considered in NHTSA's model year analysis also occur within this timeframe. Thus, NHTSA has elected to discount from the year of abatement back to the present value using constant near-term discount rates of 2.5,

[910] The Office of Management and Budget. 2023. Circular No. A-4. Regulatory Analysis. Available at: https://www.whitehouse.gov/wp-content/uploads/2023/11/CircularA-4.pdf. (Accessed: Mar. 11. 2024).

2, and 1.5 percent.[911] The 2023 EPA SC-GHG Report's central SC-GHG values are based on a 2 percent discount rate,[912] and for this reason NHTSA presents SC-GHG estimates discounted at 2 percent together with its primary estimates of other costs and benefits wherever NHTSA does not report the full range of SC-GHG estimates. Furthermore, OMB finalized an update to Circular A-4 in November 2023, in which it recommended the general application of a 2 percent rate to discount social costs and benefits (subject to regular updates), which is an estimate of consumption-based discount rate.

6.2.1.3. How NHTSA Uses the EPA Report's Estimated Social Costs of GHG Emissions

As discussed in the preceding subsections, NHTSA uses the SC-GHGs estimates found in Table A.5.1 of the 2023 EPA SC-GHG Report. These estimates, which are in dollars per-metric ton units, are multiplied by the tons of GHG emissions NHTSA forecasts to be avoided due to the final rule. **Error! Not a valid bookmark self-reference.**, **Error! Reference source not found.**, and **Error! Reference source not found.** below show the EPA report's SC-CO_2, SC-CH_4, and SC-N_2O values for the period 2020-2080. The values shown in these tables differ slightly from those reported in the 2023 EPA SC-GHG Report because they have been converted to 2021 dollars to be consistent with the remainder of the agency's analysis. For this purpose, NHTSA staff used the change in BEA's implicit price deflator for U.S. GDP between 2020 and 2021.

Table 6-12: Social Cost of Carbon Dioxide (per metric ton of CO_2, 2021$)

	Near-Term Discount Rate		
Emission Year	2.5%	2.0%	1.5%
2020	122	202	352
2021	124	206	357
2022	128	209	362
2023	131	213	367
2024	134	218	372
2025	136	222	377
2026	139	225	382
2027	142	229	387
2028	145	233	392
2029	147	236	397
2030	151	241	402
2031	154	245	407
2032	157	248	412
2033	160	252	416
2034	162	256	421
2035	165	259	427
2036	168	264	431
2037	172	268	436
2038	175	271	441
2039	178	275	446

[911] As discussed in EPA SC-GHG Report, the error associated with using a constant discount rate rather than a certainty-equivalent rate path to calculate the present value of a future stream of monetized climate benefits is small for analyses with moderate time frames (e.g., 30 years or less). The EPA SC-GHG Report also provides an illustration of the amount of climate benefits from reductions in future emissions that would be underestimated by using a constant discount rate relative to the more complicated certainty-equivalent rate path.
[912] See page 101 of the EPA SC-GHG Report (2023).

2040	181	279	451
2041	184	283	456
2042	187	288	461
2043	190	292	466
2044	195	296	472
2045	198	300	477
2046	201	304	483
2047	204	310	488
2048	208	314	494
2049	211	318	499
2050	214	322	504
2051	218	326	509
2052	221	329	514
2053	224	334	519
2054	227	338	523
2055	230	341	528
2056	232	345	533
2057	235	349	538
2058	238	353	543
2059	242	357	547
2060	245	361	552
2061	247	364	556
2062	250	367	560
2063	252	370	564
2064	255	373	568
2065	257	377	572
2066	259	380	575
2067	263	383	579
2068	265	386	584
2069	268	389	588
2070	270	392	591
2071	273	395	595
2072	275	400	599
2073	278	403	602
2074	281	406	607
2075	283	409	610
2076	287	412	614
2077	289	416	618
2078	292	419	621
2079	295	423	625

2080	297	426	629

Table 6 13: Social Cost of Methane (per metric ton CH4, 2021$)

	Near-Term Discount Rate		
Emission Year	2.5%	2.0%	1.5%
2020	1,315	1,724	2,411
2021	1,385	1,802	2,501
2022	1,454	1,881	2,592
2023	1,524	1,960	2,682
2024	1,594	2,039	2,772
2025	1,663	2,118	2,862
2026	1,733	2,197	2,952
2027	1,803	2,276	3,043
2028	1,873	2,355	3,133
2029	1,942	2,434	3,224
2030	2,012	2,513	3,314
2031	2,094	2,604	3,420
2032	2,175	2,696	3,526
2033	2,256	2,788	3,630
2034	2,337	2,880	3,736
2035	2,419	2,972	3,841
2036	2,501	3,063	3,947
2037	2,581	3,155	4,053
2038	2,663	3,247	4,157
2039	2,744	3,339	4,263
2040	2,826	3,430	4,369
2041	2,914	3,530	4,481
2042	3,003	3,630	4,595
2043	3,090	3,730	4,708
2044	3,179	3,829	4,821
2045	3,267	3,928	4,934
2046	3,356	4,028	5,048
2047	3,444	4,127	5,161
2048	3,533	4,226	5,274
2049	3,621	4,326	5,387
2050	3,710	4,425	5,501
2051	3,790	4,518	5,609
2052	3,871	4,611	5,717
2053	3,952	4,703	5,824
2054	4,033	4,796	5,932

2055	4,113	4,889	6,039
2056	4,195	4,981	6,146
2057	4,275	5,074	6,254
2058	4,356	5,168	6,362
2059	4,438	5,260	6,470
2060	4,518	5,353	6,577
2061	4,590	5,437	6,678
2062	4,662	5,522	6,777
2063	4,735	5,607	6,878
2064	4,807	5,692	6,977
2065	4,880	5,776	7,077
2066	4,952	5,861	7,177
2067	5,024	5,946	7,277
2068	5,096	6,029	7,376
2069	5,169	6,114	7,477
2070	5,241	6,199	7,576
2071	5,318	6,289	7,681
2072	5,397	6,379	7,785
2073	5,474	6,468	7,891
2074	5,552	6,557	7,996
2075	5,630	6,646	8,100
2076	5,708	6,736	8,205
2077	5,786	6,826	8,310
2078	5,864	6,915	8,415
2079	5,941	7,005	8,520
2080	6,020	7,094	8,624

Table 6-13: Social Cost of Nitrous Oxide (per metric ton N_2O, 2021$)

	Near-Term Discount Rate		
Emission Year	**2.5%**	**2.0%**	**1.5%**
2020	36,847	56,621	91,286
2021	37,839	57,903	92,944
2022	38,830	59,185	94,602
2023	39,822	60,467	96,260
2024	40,813	61,748	97,918
2025	41,805	63,030	99,576
2026	42,796	64,312	101,234
2027	43,788	65,594	102,892
2028	44,779	66,876	104,550
2029	45,771	68,157	106,208

2030	46,762	69,439	107,866
2031	47,788	70,747	109,529
2032	48,814	72,054	111,191
2033	49,840	73,361	112,854
2034	50,866	74,668	114,516
2035	51,892	75,975	116,179
2036	52,918	77,282	117,840
2037	53,943	78,590	119,503
2038	54,969	79,897	121,165
2039	55,995	81,204	122,828
2040	57,021	82,512	124,490
2041	58,183	83,986	126,348
2042	59,346	85,461	128,207
2043	60,508	86,935	130,064
2044	61,670	88,411	131,923
2045	62,833	89,886	133,781
2046	63,995	91,360	135,640
2047	65,158	92,835	137,497
2048	66,320	94,311	139,356
2049	67,482	95,785	141,214
2050	68,645	97,260	143,072
2051	69,730	98,644	144,829
2052	70,817	100,027	146,585
2053	71,902	101,411	148,342
2054	72,989	102,795	150,098
2055	74,075	104,179	151,854
2056	75,161	105,563	153,611
2057	76,247	106,947	155,367
2058	77,333	108,330	157,124
2059	78,419	109,714	158,880
2060	79,506	111,098	160,637
2061	80,447	112,309	162,196
2062	81,388	113,519	163,755
2063	82,330	114,730	165,314
2064	83,271	115,940	166,873
2065	84,212	117,151	168,432
2066	85,152	118,361	169,992
2067	86,094	119,572	171,551
2068	87,035	120,782	173,111
2069	87,976	121,993	174,670

2070	88,917	123,204	176,229
2071	89,956	124,485	177,809
2072	90,995	125,766	179,388
2073	92,034	127,047	180,967
2074	93,073	128,328	182,546
2075	94,111	129,608	184,125
2076	95,150	130,890	185,705
2077	96,188	132,171	187,284
2078	97,227	133,452	188,862
2079	98,266	134,733	190,441
2080	99,305	136,013	192,021

As discussed in the preceding section, NHTSA follows EPA's approach to discount avoided climate damages from the year of abatement to present value using the corresponding near-term constant discount rates of 2.5, 2.0, and 1.5 percent. In places where NHTSA does not present the climate benefits based on the full range of SC-GHG estimates, NHTSA presents results using the SC-GHG values based on the 2 percent near-term discount rate, which are discounted to present value using a constant 2 percent discount rate.

6.2.2. Monetized Health Impacts from Changes in Criteria Pollutant Emissions

The CAFE Model estimates monetized health effects associated with emissions from directly emitted particulate matter 2.5 microns or less in diameter ($PM_{2.5}$) and two precursors to $PM_{2.5}$ (NO_x and SO_2). As discussed in Chapter 5, although EPA currently regulates other criteria pollutants, such as carbon monoxide (CO) and ground-level ozone (O_3), we only calculate impacts from these three pollutants since they are known to be emitted regularly from mobile sources and have the most adverse effects to human health; the EPA has published several papers estimating the benefits per ton of reducing these pollutants. Other pollutants, especially those that are precursors to ozone, are more difficult to model due to the complexity of their formation in the atmosphere, and EPA does not calculate benefit-per-ton estimates for these pollutants. The CAFE Model computes the monetized impacts associated with health damages from each pollutant by multiplying monetized health impact per ton values by the total tonnage of these pollutants, which are emitted from both upstream and downstream sources. Chapter 5.2 includes a detailed description of the emission factors that inform the CAFE Model's calculation of the total tonnage of each pollutant associated with upstream and downstream emissions.

These monetized health impacts per ton values are closely related to the health incidence per ton values described in Chapter 5.4. We used the same EPA sources that provided health incidence values to determine which monetized health impacts per ton values to use as inputs in the CAFE Model. The EPA uses the Value of a Statistical Life (VSL) to estimate premature mortality impacts and a combination of WTP estimates and costs of treating the health impact for estimating the morbidity impacts.[913] EPA's 2018 technical support document, "Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors,"[914,915] contains a more detailed account of how EPA monetized those health incidences. It is important to note that the EPA's cited sources frequently refer to these monetized health impacts per ton as BPT, since they describe these estimates in terms of emissions avoided. We generally refer to these in the CAFE Model input structure as monetized health impacts or damage costs associated with pollutants emitted, not avoided, unless the context states otherwise.

[913] Although EPA and DOT's VSL values differ, DOT staff determined that using EPA's VSL was appropriate here, since it was already included in these monetized health impact values, which were best suited for the purposes of the CAFE Model.
[914] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. pp. 1-108. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: Feb. 14, 2024).
[915] Referred to here as the 2018 EPA source apportionment TSD.

The CAFE Model includes monetized impacts per ton for multiple pollutant sources – referred to here as source sectors or source categories (e.g., refineries, light truck mobile sources, electricity generation, etc.). Certain source sectors may be associated with higher monetized impacts per ton than others. Since the impacts for the different source sectors all are based on the emission of one ton of the same pollutants (NO_X, SO_X, and $PM_{2.5}$), the differences in the incidence per ton values between sectors arise from differences in the geographic distribution of the pollutants – a factor that affects the number of people impacted by the pollutants.[916]

The various emission source sectors included in the EPA papers cited did not always correspond exactly to the emission source categories used in the CAFE Model.[917] In those cases, we mapped multiple EPA sectors to a single CAFE source category and computed a weighted average of the health impact per ton values from those EPA sectors. The CAFE Model health impacts inputs are based partially on the structure of one of the EPA source papers (the 2018 EPA Source Apportionment TSD), which reported benefits per ton values for the years 2020, 2025, and 2030. For the years in between the source years used in the input structure, the CAFE Model applies values from the closest source year. For instance, the model applies 2020 monetized health impact per ton values for calendar years 2020-2022 and applies 2025 values for calendar years 2023-2027. The model applies 2030 values for calendar years 2028-2032. For more information, see the CAFE Model Documentation,[918] which contains additional details of the CAFE Model's computation of monetized health impacts.

Although EPA has published new health impact per ton values recently for various sectors, including refineries, oil and gas, and electricity-generating units, we have not used these in our analysis since the new estimates are not available for all sectors. Switching to the values that use the latest EPA methodology at this time would require leaving out multiple pollutant sectors from our analysis (petroleum transportation, fuel transportation, storage, and distribution, and mobile source sectors). While the older BPT values in our analysis slightly undervalue the benefits of reducing health emissions, removing these categories would also undervalue health emission reduction benefits.

It is important to note that uncertainties and limitations exist at each stage of the emissions-to-health benefit analysis pathway (e.g., projected emissions inventories, air quality modeling, health impact assessment, and economic valuation). The BPT approach to monetizing benefits relies on many assumptions; when uncertainties associated with these assumptions are compounded, even small uncertainties can greatly influence the size of the total quantified benefits. Some key assumptions associated with $PM_{2.5}$-related health benefits and uncertainties associated with the BPT approach are discussed above in Chapter 5.4.3.

The following subchapters describe the sources that we used to provide the CAFE Model with monetized health impacts per ton values and any calculations made in the process. Each subchapter corresponds to one of the CAFE Model's five upstream emission source sectors and the downstream emission sources.

The emission source categories defined in the CAFE Model are as follows:

- Upstream emissions sources
    - Petroleum Extraction
    - Petroleum Transportation
    - Refineries
    - Fuel Transportation, Storage, and Distribution (Fuel TS&D)
    - Electricity Generation
- Downstream emissions sources
    - On-road LD cars and motorcycles
    - On-road LD trucks

[916] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. pp. 1-108. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: Feb. 14, 2024).
[917] The CAFE Model's emission source sectors follow a similar structure to the inputs from GREET. See Chapter 5.2 for further information.
[918] NHTSA. 2022. CAFE Compliance and Effects Modeling System: The Volpe Model. Last Revised: 2022. Available at: https://www.nhtsa.gov/corporate-average-fuel-economy/cafe-compliance-and-effects-modeling-system. (Accessed: Feb. 14, 2024).

- On-road LD diesel

Table 6-14 details how we mapped between CAFE Model and EPA emission source sectors.

Table 6-14: CAFE to EPA Emissions Source Sector Mapping

CAFE Model Upstream Component (per GREET)	Corresponding EPA Source Categories
Petroleum Extraction	Assigned to the "Oil and natural gas" sector from a 2018 EPA paper (Fann et al.).[919]
Petroleum Transportation	Assigned to several mobile source sectors from a 2019 EPA paper (Wolfe et al.)[920] and one source sector from the 2018 EPA source apportionment TSD.[921] The specific mode mappings are as follows: From Wolfe et al: • Rail sector (for GREET's rail mode) • C1&C2 marine vessels sector (for GREET's barge mode) • C3 marine vessels sector (for GREET's ocean tanker mode) • On-road heavy-duty diesel sector (for GREET's truck mode) From the 2018 EPA source apportionment TSD: • Electricity generating units (for GREET's pipeline mode) A weighted average of these different sectors was used to determine the overall health impact values for the sector as a whole.
Fuel TS&D	Assigned to several mobile source sectors from a 2019 EPA paper (Wolfe et al.)[922] and one source sector from the 2018 EPA source apportionment TSD. The specific mode mappings are as follows: From Wolfe et al.: • Rail sector (for GREET's rail mode) • C1&C2 marine vessels sector (for GREET's barge mode) • C3 marine vessels sector (for GREET's ocean tanker mode) • On-road heavy-duty diesel sector (for GREET's truck mode) From the 2018 EPA source apportionment TSD: • Electricity generating units (for GREET's pipeline model) A weighted average of these different sectors was used to determine the overall health impact values for the sector as a whole.
Electricity Generation	Assigned to the electricity-generating units' sector from the 2018 EPA source apportionment TSD.[923]

[919] Fann et al. 2018. Assessing Human Health $PM_{2.5}$ and Ozone Impacts from U.S. Oil and Natural Gas Sector Emissions in 2025. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6718951. (Accessed: Feb. 14, 2024).
[920] Wolfe et al. 2019. Monetized health benefits attributable to mobile source emissions reductions across the United States in 2025. Available at: https://pubmed.ncbi.nlm.nih.gov/30296769. (Accessed: Feb. 14, 2024). Health incidence per ton values corresponding to this paper were sent by EPA staff.
[921] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. pp. 1-108. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: Feb. 14, 2024).
[922] Wolfe, P. et al. 2019. Monetized Health Benefits Attributable to Mobile Source Emission Reductions Across the United States in 2025. *The Science of the Total Environment*. Vol. 650(2): pp. 2490–98. Available at: https://pubmed.ncbi.nlm.nih.gov/30296769/. (Accessed: Feb. 14, 2024).
[923] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. Pages 1-108. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: Feb. 14, 2024).

6.2.2.1. Monetized Health Impacts per Ton Associated with the Petroleum Extraction Sector

We matched the monetized health impact per ton values for the petroleum extraction sector with a 2018 oil and natural gas sector paper (Fann et al.), which estimated monetized health impacts for this sector in the year 2025.[924] Fann et al. defined emissions from the oil and natural gas sector as not only arising from petroleum extraction but also from transportation to refineries, while the CAFE/GREET component is composed of only petroleum extraction. We consulted with the authors of the EPA 2018 TSD and determined that this paper (Fann et al.) contained the best available estimates for the petroleum extraction sector, notwithstanding this difference. Therefore, these monetized values may slightly overestimate the cost of health impacts associated with emissions from this sector.

Fann et al. reported monetized health impact per ton values discounted at 3 percent, while the CAFE Model reports total health impact costs discounted at both 3 and 7 percent.[925] In order to match the structure of other health impact costs in the CAFE Model, we developed proxies for the 7 percent discounted values, using the ratio between a comparable sector's 3 and 7 percent discounted values. From the 17 sectors discussed in the 2018 EPA source apportionment TSD, the taconite mines sector most closely resembled the petroleum extraction sector in emission location characteristics, as both occur largely in rural areas.[926]

Fann et al. estimated monetized health impacts per ton values only for calendar year 2025, so we applied these values to all three years in the CAFE Model health impacts input structure: 2020, 2025, and 2030.[927] This implies an overestimation of damages in earlier years and an underestimation in 2030.

All monetized health impact per ton estimates reported by Fann et al. used 2015$. We used implicit price deflators from the BEA to convert the estimates to 2021$ to be consistent with the rest of the CAFE Model inputs.[928]

6.2.2.2. Monetized Health Impacts per Ton Associated with Petroleum Transportation Sector

We used the weighted average calculation – also used to determine the appropriate health incidence per ton values (see Chapter 5.4.1) – for the petroleum transportation sector when estimating the monetized health impacts per ton values. The same sources and calculations are used with the only difference being that this subchapter deals strictly with monetized impacts per ton as opposed to incidences.

The petroleum transportation sector does not correspond to any single EPA source sector, so we used a weighted average of multiple different EPA sectors to determine the monetized health impact per ton values for the petroleum transportation sector as a whole. In calculating the weighted average, we mapped the petroleum transportation sector as described in GREET to a combination of different EPA mobile source sectors from two different papers, the 2018 EPA source apportionment TSD[929] and a 2019 mobile source sectors paper (Wolfe et al.).[930] See Table 6-14 for the exact mapping.

Wolfe et al. included more specific sectors than the 2018 EPA source apportionment TSD; for instance, where 'Aircraft, Locomotive, and Marine Vessels' is a single category in the 2018 EPA source apportionment TSD, Wolfe et al. specify four: Aircraft, Rail, C1 & C2 Marine Vessels, and C3 Marine Vessels. Therefore, we used

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[924] Fann et al. 2018. Assessing Human Health $PM_{2.5}$ and Ozone Impacts from U.S. Oil and Natural Gas Sector Emissions in 2025. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6718951. (Accessed: Feb. 14, 2024).

[925] Fann et al. 2018. Assessing Human Health $PM_{2.5}$ and Ozone Impacts from U.S. Oil and Natural Gas Sector Emissions in 2025. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6718951. (Accessed: Feb. 14, 2024).

[926] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. pp. 1-108. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: May 31, 2023).

[927] These three years are used in the CAFE Model structure for health impact per ton values because it was originally based on the estimates provided in the 2018 EPA source apportionment TSD.

[928] BEA. Table 1.1.9. Implicit Price Deflators for Gross Domestic Product. BEA. Available at: https://apps.bea.gov/iTable/?reqid=19&step=3&isuri=1&1921=survey&1903=13. (Accessed: Feb. 14, 2024).

[929] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. pp. 1-108. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: Feb. 14, 2024).

[930] Wolfe, P. et al. 2019. Monetized Health Benefits Attributable to Mobile Source Emission Reductions Across the United States in 2025. *The Science of the Total Environment.* Vol. 650(2): pp. 2490–98. Available at: https://pubmed.ncbi.nlm.nih.gov/30296769/. (Accessed: Feb. 14, 2024).

sectors from Wolfe et al. wherever possible and used the 2018 EPA source apportionment TSD for the transportation mode mapping only when there were no appropriate sectors in the Wolfe et al. paper. Wolfe et al. only report impacts for the year 2025, but we determined that these values could be applied to the other years in the input structure, after communication with one of the authors at EPA. Therefore, this implies a slight overestimation of monetized health impacts in 2020 and a slight underestimation of monetized impacts in 2030.

We calculated the total monetized health costs per ton by pollutant using a weighted average of these different sectors, based on the percent of upstream emissions attributable to each transportation mode.

In GREET – the model that informs the CAFE Model upstream component categories – there are five types of petroleum products relevant to upstream emissions for gasoline:

- Conventional crude oil
- SCO
- Dilbit
- Shale oil (Bakken)
- Shale oil (Eagle Ford)

Table 6-15: Petroleum Transportation Mode Shares in 2025[931]

Fuel Type[932]	Ocean Tanker	Barge	Pipeline	Rail	Truck
Conventional Crude Oil	2.7%	23.3%	74%	-	-
Synthetic Crude Oil (SCO)	-	-	100%	-	-
Dilbit	-	-	100%	-	-
Shale Oil (Bakken)	-	-	50%	50%	100%
Shale Oil (Eagle Ford)	-	20%	65%	15%	100%

GREET provided the percentage of these five petroleum products transported by each mode, as shown in Table 6-15. Transportation both within the United States and outside of U.S. borders is included, provided that the destination of the transported products is the continental United States. The percentages add up to more than 100 percent because there are multiple stages of the transportation journey. For example, 50 percent of shale oil (Bakken) is transported by pipeline and the other 50 percent by rail during the first part of the journey to the refinery, but 100 percent of it is transported by truck on the second part of the journey.

GREET also provided emissions in grams/mm Btu of fuel transported attributable to each transportation mode. We multiplied these emissions values by the percentage of petroleum product transported by each mode, as seen in Table 6-15, to obtain a weighted value. This calculation uses total emissions from each mode for all modes except ocean tanker. Health effects from ocean transport are concentrated in populated areas, rather than while the tankers are at sea. To address this, the ocean tanker mode includes only urban emissions. Additionally, using urban emissions for ocean tankers ensures that the emissions attributable to this mode are not underestimated, because the percentage of related health impacts decreases when using the high total emissions figure.

[931] These values are from the GREET 2023 Model, using baseline year 2025. In the Excel version, this information can be found in the T&D Flowcharts worksheet. See https://greet.es.anl.gov/ to download the model.
[932] Conventional crude oil is both extracted domestically and imported. SCO and Dilbit are oil sand products and are imported exclusively from Canada. Shale oil is exclusively domestic. See the 'T&D Flowcharts' worksheet in the GREET Model.

We multiplied emissions by transportation mode share five times, once for each of the five petroleum types. Since the GREET Model projects that the transportation mode shares will change over time, different weights are used for years 2020, 2025, and 2030, based on the mode percentages GREET reports for those years.[933]

Table 6-16: Energy Share by Petroleum Type[934]

Conventional Crude Oil	SCO	Dilbit	Shale (Bakken)	Shale (Eagle Ford)
79.1%	3.5%	5%	6.5%	5.9%

We then multiplied the energy share of each petroleum type by its corresponding emissions value to reflect how much of each emissions value should go into the weighted average. For example, using the energy share information in Table 6-16, we multiply the conventional crude emissions by 79.1 percent, the SCO emissions by 3.5 percent, the Dilbit emissions by 5 percent, the shale (Bakken) emissions by 6.5 percent, and the shale (Eagle Ford) emissions by 5.9 percent.

Next, we summed the resulting weighted emissions values by pollutant to represent the total upstream emissions in grams/mmBtu of petroleum product transported. With that information, we can calculate the percentages of each pollutant attributable to each mode for petroleum transportation overall. We calculated these percentages three times, for each different base year (2020, 2025, and 2030); Table 6-17 shows these percentages, using base year 2020 as an example.

Table 6-17: Percent of Emissions Attributable to Each Mode for the Petroleum Transportation Category[935]

Mode	EPA Source Category	NO_X	SO_X	$PM_{2.5}$
Ocean Tanker	C3 marine vessels	24.05%	50.31%	37.23%
Barge	C1 & C2 marine vessels	49.66%	1.17%	30.72%
Pipeline	Electricity-generating units	18.78%	48.17%	29.51%
Rail	Rail	6.63%	0.25%	2.26%
Truck	On-road heavy-duty diesel	0.88%	0.10%	0.28%

Finally, we calculated the weighted average of monetized health impacts by multiplying the percentages of emissions by mode by the *monetized* health costs per ton from the relevant EPA sector that matches each mode. Equation 6-10 illustrates this process, using incidences of asthma exacerbation as an example. The variables beginning with "%" represent the percent of SO_X emissions attributable to each specified mode. The other variables indicate the incidences per ton resulting from SO_X emissions coming from each sector: *C3marine* corresponds to C3 marine vessels, *C1&C2* marine to C1 & C2 marine vessels, *EGU* corresponds to electricity-generating units, *Rail* to railroad, and *Truck* corresponds to on-road heavy-duty diesel.

Equation 6-10: Weighted Average of Health Incidences from the Petroleum Transportation Sector

$$\text{Asthma Exacerbation incidents per ton from } SO_X \text{ in Petroleum Transportation=}$$

$$(\%SO_X \text{ ocean tanker} \times \text{C3marine}) + (\%SO_X \text{ barge} \times \text{C1\&C2 marine}) +$$
$$(\%SO_X \text{ pipeline} \times \text{EGU}) + (\%SO_X \text{ rail} \times \text{Rail}) + (\%SO_X \text{ truck} \times \text{Truck})$$

933 These are the three years used in the CAFE Model inputs for health impacts, based on the structure of the 2018 EPA source apportionment TSD that originally informed the analysis. Baseline years may be changed in the 'Inputs' worksheet in the GREET Model. Although the base year in the CAFE analysis is 2022, we extend the 2020 health impacts values to 2022, and use 2025 and 2030 values for subsequent years.
934 Taken from the Petroleum tab of the GREET Excel Model, using 2025 as a base year.
935 These percentages are calculated using the 2025 base year in GREET.

Following guidance from the 2018 EPA source apportionment TSD, we rounded the final health impact costs per ton to two significant digits.[936]

6.2.2.3. Monetized Health Impacts per Ton Associated with the Fuel Transportation, Storage, and Distribution Sector

As in the case of the previous subchapter, this subchapter closely echoes the approach taken in the corresponding Fuel TS&D subchapter in Chapter 5.4, since we calculated the monetized health impacts per ton described in this subchapter using the same sources and the same weighted averaging process. The Fuel TS&D sector, like the Petroleum Transportation sector, corresponds to several different EPA source sectors, so we used the same weighted average approach as described in Chapter 6.2.2.2. Gasoline blendstocks and finished gasoline are the two components of the Fuel TS&D category described in GREET. We mapped these components to five different transportation source sectors from two EPA papers – the 2018 EPA source apportionment TSD and the 2019 mobile source emission sectors paper, Wolfe et al.[937]

GREET provided the percentage of each fuel type transported by each mode, and as in the case of the petroleum transportation calculations, the percentages change based on the year. In the case of the "gasoline blendstocks" fuel type, the mode shares add up to more than 100 percent because multiple modes are taken during the distinct parts of the trip. As an example, Table 6-18 shows the estimated mode shares in 2020.

Table 6-18: Transportation Mode Shares for the Fuel TS&D Sector[938]

Mode Share	Gasoline Blendstocks	Finished Gasoline
Ocean Tanker	0.0%	-
Barge	31.2%	-
Pipeline	66.6%	-
Rail	2.2%	-
Truck	100%	100%

We multiplied the emissions by pollutant attributed to each mode (measured in grams/mmBtu) by these mode share percentages to create weighted emissions values.

Next, we added the weighted emissions from trucks transporting gasoline blendstocks to the emissions arising from finished gasoline transportation (100 percent truck mode). Using that information, we calculated the total emissions per pollutant to find the percentage of emissions attributable to each mode for Fuel TS&D overall. Table 6-19 provides an example of these percentages.

Table 6-19: Percent of Emissions Attributable to Each Mode for the Fuel TS&D Category[939]

Mode	EPA Source Category	NO_X	SO_X	$PM_{2.5}$
Ocean Tanker	C3 marine vessels	0.00%	0.00%	0.00%
Barge	C1 & C2 marine vessels	72.34%	8.52%	72.99%

[936] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. p. 14. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: Feb. 14, 2024).

[937] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. p. 14. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: Feb. 14, 2024); Wolfe, P. et al. 2019. Monetized Health Benefits Attributable to Mobile Source Emission Reductions Across the United States in 2025. *The Science of the Total Environment*. Vol. 650(2): pp. 2490–98. Available at: https://pubmed.ncbi.nlm.nih.gov/30296769/. (Accessed: May 31, 2023).

[938] Using baseline year 2025 in GREET. These values can be found in the 'T&D Flowcharts' tab of the GREET Model.

[939] These percentages are calculated using the 2025 base year in GREET.

Pipeline	Electricity-generating units	6.16%	79.06%	15.80%
Rail	Rail	0.86%	0.16%	0.48%
Truck	On-road heavy-duty diesel	20.64%	12.26%	10.73%

We followed the same process for Fuel TS&D calculations as the petroleum transportation category, matching the modes to EPA sectors and using the calculated percentages to create a weighted average of monetized health impacts associated with emissions of each pollutant. We completed these calculations three times, for years 2020, 2025, and 2030.[940] As stated previously, the sectors in the 2019 mobile sources paper only showed monetized health costs per ton estimated for the year 2025, but we determined that this information should be applied to all years, as it was the most up-to-date available.[941] The use of 2025 monetized impacts for all three years implies a slight overestimation of monetized health impacts in 2020 and a slight underestimation in 2030.

Wolfe et al. reported all monetized impacts per ton values in 2015$. We used BEA deflators to convert these values to 2021$ to ensure consistency with the rest of the CAFE Model inputs.[942]

6.2.2.4. Monetized Health Impacts per Ton Associated with the Refineries Sector

We matched the monetized health impacts per ton values associated with the refineries sector in the 2018 EPA source apportionment TSD to the petroleum refining emissions category in the CAFE Model. We used BEA deflators to convert the values to 2021$.[943] Table 6-20 shows the various types of health effects per ton corresponding to each pollutant emitted from the refineries sector. These estimates are based on the study cited in the 2018 EPA source apportionment TSD.[944]

Table 6-20: Monetized (2021$) Health Impacts per Ton from Refineries, 3% Discount Rate[945]

Calendar Year	Upstream Emissions (Refineries Sector)		
	NO_X	SO_X	$PM_{2.5}$
2020	$8,700	$87,000	$410,000
2025	$9,500	$97,000	$450,000
2030	$10,000	$110,000	$490,000

6.2.2.5. Monetized Health Impacts per Ton Associated with the Electricity Generation Sector

The 2018 EPA source apportionment TSD contains monetized health impacts per ton values associated with emissions of NO_X, SO_X, and $PM_{2.5}$ arising from electricity-generating units (EGUs), reported in 2015$. We mapped these to the electricity generation sector in the CAFE Model and converted the values to 2021$ using BEA deflators to ensure consistency with the rest of the CAFE Model inputs.[946] Table 6-21 shows the health effects per ton associated with the emissions of criteria pollutants from this sector.

[940] Although the base year in the CAFE analysis is 2022, we extend the 2020 health impacts values to 2022, and use 2025 and 2030 values for subsequent years.
[941] We communicated with an author of the paper at EPA to help inform our decision.
[942] BEA. Table 1.1.9. Implicit Price Deflators for Gross Domestic Product. BEA. Available at: https://apps.bea.gov/. (Accessed: Feb. 14, 2024).
[943] BEA. Table 1.1.9. Implicit Price Deflators for Gross Domestic Product. BEA. Available at: https://apps.bea.gov/. (Accessed: Feb. 14, 2024).
[944] EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. Office of Air and Radiation and Office of Air Quality Planning and Standards. Research Triangle Park, NC. p. 14. Available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: May 31, 2023).
[945] Based on the Krewski et al values in the 2018 EPA TSD. See Section II.F of the preamble for further discussion of the benefit-per-ton reporting.
[946] BEA. Table 1.1.9. Implicit Price Deflators for Gross Domestic Product. BEA. Available at: https://apps.bea.gov/. (Accessed: Feb. 14, 2024).

Table 6-21: Monetized (2021$) Health Impacts per Ton from Electricity-Generating Units, 3 Percent Discount Rate[947]

Calendar Year	Upstream Emissions (Electricity Generation Sector)		
	NO_X	SO_X	$PM_{2.5}$
2020	$7,000	$48,000	$170,000
2025	$7,600	$52,000	$190,000
2030	$8,200	$56,000	$200,000

6.2.2.6. Monetized Health Impacts per Ton Associated with Downstream Emissions

The CAFE Model follows a similar process for computing monetized health impacts resulting from downstream emissions as it does for calculating monetized health impacts from the upstream emissions sectors. We relied on a 2019 paper (Wolfe et al.) that computed monetized per ton damage costs for mobile sources in several categories, based on vehicle type and fuel type. Wolfe et al. did not report incidences per ton, but that information was obtained through communications with EPA staff who co-authored the paper. We matched three light-duty source categories and two heavy-duty source categories from the 2019 paper to the CAFE Model downstream emissions inventory: “on-road LD gas cars and motorcycles,” “on-road LD gas trucks,” “on-road LD diesel”, “on-road heavy-duty diesel”, and “on-road heavy-duty gas.” Table 6-22 shows the monetized impacts by criteria pollutant for these five categories. As in the case of the other monetized impacts from Wolfe et al., we used BEA deflators to convert monetized values from 2015$ to 2021$.[948]

Table 6-22: Monetized (2021$) Impacts per Ton from Downstream Source Categories, 3% Discount Rate

	On-road light-duty gas cars	On-road light-duty gas trucks	On-road light-duty diesel	On-road heavy-duty gas	On-road heavy-duty diesel
NO_x	$8,100	$7,400	$6,500	$6,900	$7,000
SO_x	$140,000	$110,000	$340,000	$160,000	$300,000
$PM_{2.5}$	$790,000	$670,000	$550,000	$610,000	$470,000

The CAFE Model also calculates the criteria pollutant emissions resulting from brake and tire wear. These emissions are grouped with downstream emissions and monetized using the same BPT values.

6.2.3. Social Costs of Congestion and Noise

The additional driving of new cars, light trucks, and HDPUVs that results via the fuel economy rebound effect will add slightly to the levels of traffic congestion and roadway noise caused by current motor vehicle use. The resulting increases in delays to vehicles traveling in congested traffic, together with the effects of added noise on residents of areas surrounding roadways, impose additional economic costs that are attributable to the agency’s action to establish higher fuel economy and fuel efficiency standards. Only a small fraction of these increases in delay and noise is likely to be experienced by the buyers of new vehicles whose decisions about how much more to drive – and where and when to do so – cause them. Thus, the agency’s analysis treats these increases in the costs of congestion delays and noise impacts as external costs from requiring higher fuel economy and fuel efficiency, as distinguished from private costs such as the higher prices buyers of new vehicles will pay.

To estimate the economic costs associated with increases in congestion delays and roadway noise caused by increased rebound effect driving, the agency uses estimates of incremental (or “marginal”) congestion and

[947] Based on the Krewski, et al. values in the 2018 EPA TSD. See Section II.F of the preamble for further discussion of the benefit-per-ton reporting.
[948] BEA. Table 1.1.9. Implicit Price Deflators for Gross Domestic Product. BEA. Available at: https://apps.bea.gov/. (Accessed: Feb. 14, 2024).

noise costs from increased automobile and light truck use that were originally developed by FHWA as part of its 1997 Highway Cost Allocation Study. The marginal congestion cost estimates reported in the 1997 FHWA study were intended to measure the costs of increased congestion resulting from incremental growth in automobile and light truck use and the delays it causes to drivers, passengers, and freight shipments.

As the 1997 study explained, the distinction between marginal and average congestion costs is extremely important: while average congestion costs on a roadway are calculated as total congestion costs experienced by all vehicles divided by the total number of miles they travel, marginal congestion costs are calculated as the *additional* congestion costs resulting from an incremental increase in the number of vehicle miles traveled. When roads are already crowded, marginal congestion costs can be much higher that their average value, because while each additional vehicle slows travel speeds only slightly, these slower speeds delay very large numbers of vehicles, so the resulting increase in *total* delay to all vehicles on the road can be surprisingly large. Consequently, the increases in congestion and delays associated with additional driving are generally far more than proportional to the changes in traffic volumes that cause them.

The 1997 FHWA study's estimates of marginal noise costs reflected the variation in noise levels resulting from incremental changes in travel by autos and light trucks and the estimated economic value of annoyance and other adverse impacts from noise. These effects are experienced largely by residents of the surrounding area, pedestrians and other road users not riding in motor vehicles, as well as occupants of other vehicles sharing roads with those generating noise.

Because the alternatives the agency is analyzing will each require increases in the fuel economy of new cars and light trucks, and in the fuel efficiency of HDPUVs produced in future model years, the number of miles they will be driven is likely to increase from the baseline under each alternative. To calculate the incremental costs of congestion and noise caused by this added driving, the agency multiplies FHWA's "middle" estimates of marginal congestion and noise costs per mile of auto and light truck travel by the increase in new car and light truck travel. The agency updated the original 1997 FHWA estimates of congestion costs to account for changes in travel activity and economic conditions since they were originally developed, as well as to express them in 2021 dollars for consistency with other economic inputs. NHTSA uses its updated estimates of the contribution of increased use of light-duty trucks to congestion and noise to estimate increased costs resulting from additional use of HDPUVs.

One factor affecting marginal congestion costs from additional travel is the relationship of traffic volumes to roadways' vehicle-carrying capacity, which determines how travel speeds and delays will change in response to incremental growth in traffic. When current traffic volumes are already close to a road's capacity, even a modest increase in the number of vehicles can slow travel speeds and increase delays significantly. The agency assumes that the contribution of added traffic to current congestion and delays has grown in proportion to the increase in annual vehicle miles of travel per lane-mile on major U.S. highways since 1997, the date of FHWA's original estimates of marginal congestion costs, Other important changes contributing to higher marginal costs of congestion include growth in the typical number of occupants riding in each vehicle and the economic value of their travel time, since these combine to determine the hourly economic cost of congestion delays. The agency estimated growth in the hourly cost of increased delays between 1997 and 2017 by combining escalation in the DOT-recommended value of travel time with the change in average occupancy of cars and light trucks.[949,950]

Table 6-23 reports the changes in each of the factors contributing to increased congestion costs between 1997 and 2017. The agency applied these adjustments to FHWA's 1997 estimates of marginal congestion costs to update their original values to approximate the increase in congestion costs likely to be caused by added rebound effect driving under current travel conditions. Expressed in 2021 dollars for consistency with the other economic values used to analyze this final rule, the agency's updated values of external congestion

[949] This update used 2017 rather than a more recent year for its endpoint because the last reliable estimates of vehicle occupancy are from the 2017 National Household Travel Survey Available at: https://nhts.ornl.gov/.

[950] Some commenters on the agency's previous CAFE rulemaking suggested that congestion levels on U.S. roadways may not have grown to the extent indicated by the procedure used to update FHWA's 1997 estimates of their costs. NHTSA's analysis indicate an 18% increase in congestion levels (as approximated by annual vehicle miles per lane-mile or roads and highways), while the other most widely cited source of congestion and delay estimates reports that they grew 44% in the nation's 101 largest urban areas and 37% in all 494 U.S. urban areas over that same period, so the agency's estimate appears to be conservative. See Texas Transportation Institute. Urban Mobility Report Historical Database. Available at: https://mobility.tamu.edu/umr/data-and-trends/.

costs are $0.112 per vehicle mile of increased travel by cars, and $0.100 per vehicle mile for light trucks and HDPUVs. (Increases in light truck use contribute slightly less to congestion costs than do increases in automobile driving, because light trucks tend to be driven more in suburban and rural areas where roads are typically less congested.)

Table 6-23: Factors Contributing to Increased Congestion Costs

Factor	1997 Value	Updated Value	Change
Annual VMT per Highway Lane-Mile	310,782	366,473	18%
Average Vehicle Occupancy (persons)	1.61	1.66	3%
Hourly Value of Time per Vehicle Occupant (all vehicles; 2021$)	$ 15.90	$ 19.10	20%
All Factors Combined	--	--	45%

The agency adjusted FHWA's 1997 estimate of marginal noise costs only to account for inflation since their original publication, because little research is available to indicate how noise levels or the economic costs they impose have changed since that time. Because marginal noise costs are so small—less than $0.001 per mile of additional travel for both cars and light trucks—the change in noise resulting from the final rule would have only a minimal impact. The agency's estimates of incremental congestion and noise costs from added car and light truck use are assumed to remain constant (in real or inflation-adjusted terms) throughout the analysis period. This probably causes increases in their future values due to added rebound effect driving to be underestimated, since baseline levels of congestion delays and vehicles noise are likely to continue growing over the future.

6.2.4. Benefits from Increased Energy Security

U.S. consumption and imports of petroleum products have three potential effects on the domestic economy that are often referred to as "energy security externalities," and increases in their magnitude are sometimes cited as potential social costs of increased U.S. demand for petroleum. First, any increase in global petroleum prices that results from higher U.S. gasoline demand will cause a transfer of revenue from consumers of petroleum products to oil producers worldwide, because consumers throughout the world are ultimately subject to the higher global prices for petroleum and refined products that results. Under competitive market assumptions, this transfer is simply a shift of resources that produces no change in global economic output or welfare. Since the financial drain it produces on the U.S. economy may not be considered by individual consumers of petroleum products, it is sometimes cited as an external cost of increased U.S. petroleum consumption even though it does not meet the formal definition of an externality.[951] To the degree that global petroleum suppliers like Organization of the Petroleum Exporting Countries (OPEC) and Russia exercise market power, oil market prices will be above competitive market levels, and will generate a loss in potential GDP.[952] In this situation, increases in U.S. gasoline demand will drive petroleum prices further above competitive levels, thus exacerbating this deadweight loss.

[951] The United States became a net exporter of oil on a weekly basis several times in late 2019, and EIA's subsequent analyses continue to project that it will do so on a sustained, long-term basis after 2020; see EIA. AEO 2022 Reference Case, Table 11. Available at: https://www.eia.gov/outlooks/aeo/data/browser/#/?id=11-AEO2023&sourcekey=0. As the United States has approached self-sufficiency in petroleum production, this transfer of revenue has increasingly been from U.S. consumers of refined petroleum products to U.S. petroleum producers, so any price increase that results from increased domestic petroleum demand not only leaves welfare unaffected, but even ceases to be a financial burden on the U.S. economy. In fact, as the United States has become a net petroleum exporter (AEO 2022 projects the nation to be a net exporter of petroleum and other liquids through 2050), the transfer from global consumers to petroleum producers created by higher world oil prices provides a net financial benefit to the U.S. economy. Uncertainty about the nation's long-term import-export balance makes it difficult to project precisely how this situation might change in response to changes in U.S. domestic consumption of petroleum products, but the important point is that changes in revenue flows resulting from variation in global petroleum prices are not a measure of economic costs or benefits that can be attributed to policies that affect petroleum demand.

[952] Greene, D. 2010. Measuring Energy Security: Can the United States Achieve Oil Independence? *Energy Policy*. Vol. 38(4): pp. 1614-21. Available at: https://www.osti.gov/etdeweb/biblio/21318119. (Accessed: Feb. 14, 2024).

Increased U.S. consumption of refined products such as gasoline can also expose domestic users of petroleum products to added economic risks by increasing the likelihood of sudden changes in their prices or interruptions in their supply. Users of petroleum products are unlikely to consider any effect their own consumption has on other consumers, so the expected economic cost of that increase in risk is often cited as an external cost of increased U.S. petroleum consumption.

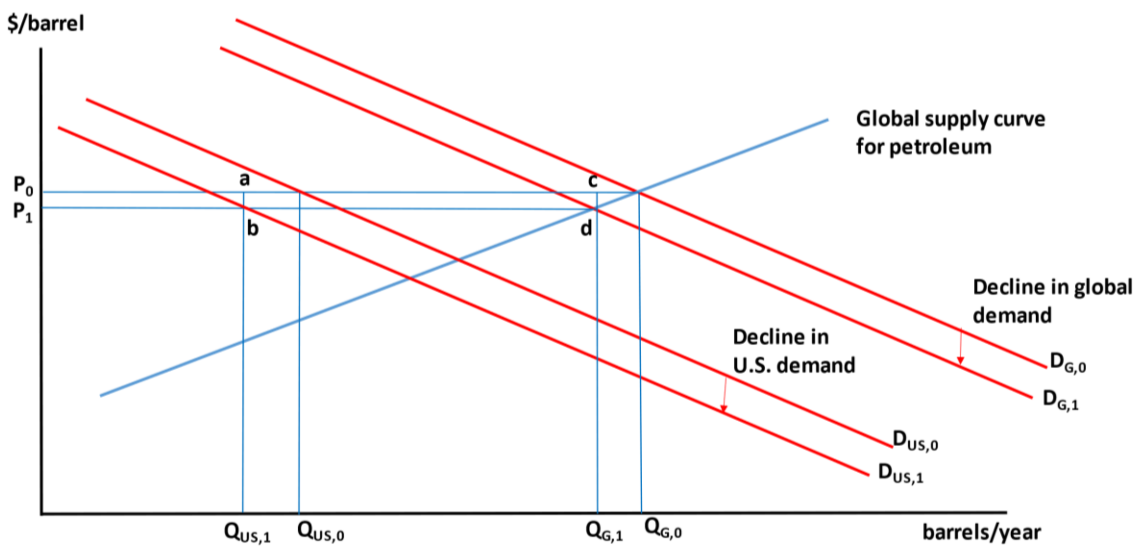
Finally, some analysts argue that domestic demand for imported petroleum may also influence U.S. military spending; because any increase in the cost of military activities necessary to enable additional petroleum imports would not be reflected in the price paid at the gas pump, this effect is often asserted to represent a third category of external costs from increased U.S. petroleum consumption.

This subchapter assesses the extent to which each of these costs is likely to change as a result of establishing stricter standards, identifies whether that change would represent a real economic benefit for the United States (or simply reduce transfers of resources), and describes how the agency measures any resulting benefits and incorporates them into its analysis. Our current analysis quantifies the *incremental* effect of more stringent fuel economy standards on costs related to energy security; while these are likely to be modest when compared to the overall long-term cumulative impact of fuel economy and fuel efficiency standards on energy security, they will nevertheless add significantly to that cumulative effect.

6.2.4.1. U.S. Petroleum Demand and its Effect on Global Prices

Figure 6-4 illustrates the effect of a decrease in U.S. fuel and petroleum demand on worldwide demand for petroleum and its global market price under competitive market conditions. The reduction in domestic demand from adopting more stringent standards is represented by an inward shift in the U.S. demand curve for petroleum from its initial position at $D_{US,0}$ with the baseline standards in effect, to $D_{US,1}$ with higher standards replacing them. Because global petroleum demand is simply the sum of what each nation would purchase at different prices, the inward shift in U.S. demand causes an identical inward shift in the global demand curve, as the figure shows.[953]

Figure 6-4: U.S. Petroleum Demand and its Effect on Global Prices



The global supply curve for petroleum shown in Figure 6-5 slopes upward, reflecting the fact that it is progressively more costly for oil-producing nations to explore for, extract, and deliver additional supplies of oil

[953] The figure exaggerates the U.S. share of total global consumption, which currently stands at about 20 percent, for purposes of illustration.

to the world market.[954] Thus the downward shift in the U.S. and world demand curves leads to a decrease in the global price for oil, from P_0 to P_1 in the figure.[955] Lower prices partly offset the effect of declining demand on consumption, but on balance lower domestic demand reduces U.S. purchases of petroleum from $Q_{US,0}$ to $Q_{US,1}$, and global consumption from $Q_{G,0}$ to $Q_{G,1}$. The resulting savings to U.S. consumers consist mainly of what they previously spent to purchase the quantity they no longer consume, which is measured by the product of the original price P_0 and the decline in domestic consumption ($Q_{US,0} – Q_{US,1}$). However, this saving is a purely private (or "internal") consequence of declining U.S. demand, since it is experienced directly by consumers and in proportion to their respective reductions in purchases of petroleum products.

At the same time, however, the decline in the global price of petroleum means that domestic consumers also save that amount on each barrel they *continue* to buy—including drivers of vehicles already on the road; their resulting savings is the product of the decline in price (P_0-P_1) and the amount they continue to use ($Q_{US,1}$), or the area P_0abP_1.[956,957] This additional savings is sometimes cited as an economic benefit of U.S. conservation measures such as raising standards stemming from a reduction in the external costs drivers impose on one another, but is more properly interpreted as reducing the transfer of revenue from U.S. consumers to petroleum producers worldwide. Reducing this transfer is thus a purely "pecuniary" externality resulting from lower U.S. demand, which has no effect on total economic output or welfare within or outside the United States.[958] However, as noted above, this analysis focuses on impacts to U.S. consumers, and as such, the benefit to U.S. consumers of lower oil prices caused by enhanced fuel economy is important to acknowledge.

Much of the reduction in payments by domestic users of petroleum products would once have represented a loss to foreign-owned oil producers and would thus have reduced the financial drain on the U.S. economy from using and importing petroleum. To a growing extent, however, lower payments by U.S. consumers that result from downward pressure on the world oil price are a transfer *entirely within* the Nation's economy, as the volume of petroleum supplied by U.S. producers exceeds the level of domestic consumption. The United States recently became a net exporter of petroleum, and as it approached that situation an increasing share of any savings to U.S. petroleum consumers resulting from lower global oil prices became a financial loss to U.S. oil producers.[959] Once the United States became self-sufficient in petroleum supply (which occurred in 2020), the savings to U.S. petroleum users that results from reducing oil prices effectively reduced a transfer from domestic petroleum consumers to domestic producers. Thus, the financial burden that revenue transfers from U.S. consumers to foreign oil producers once placed on the U.S. economy has been eased and ultimately erased by growing U.S. petroleum production, so curtailing domestic demand no longer reduces that burden.[960]

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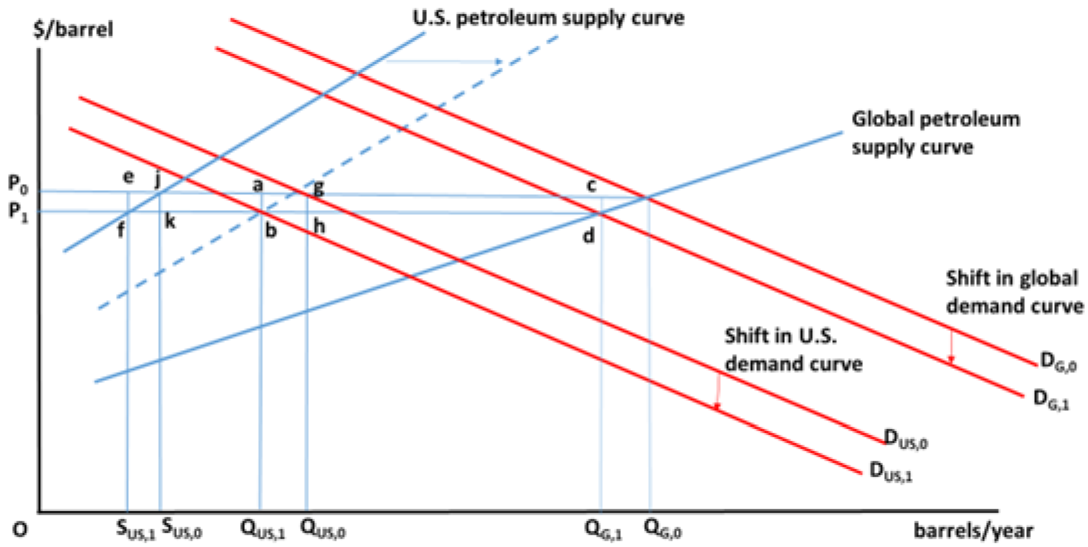
[954] The figure depicts the relationship between the global supply of petroleum and its worldwide price during a single time period. The global supply curve for petroleum has been shifting outward over time in response to increased investment in exploration, the ability of refineries to utilize feedstocks other than conventional petroleum, and technological innovations in petroleum extraction. The combination of these developments may also have reduced its upward slope, meaning that global supply now increases by more in response to increases in the world price than it once did, and that increasing global demand causes smaller price increases. However, if large oil producers control a sufficient fraction of global oil production to enable them to raise prices above competitive levels, the globaly supply curve will lie above the marginal cost curve because it will reflect market power of the colluding producers.
[955] While U.S. demand influences prices, price is determined by the interaction of global demand and supply.
[956] Foreign petroleum users also pay the lower global price P_1 for each barrel they continue to consume, so in total they save (P_0-P_1) times ($Q_{G,1} – Q_{US,1}$) or the area acdb in the figure, as a consequence of reducing U.S. demand.
[957] Sometimes this benefit is expressed in terms of per barrel of reduced domestic consumption. Under this approach, the amount is expressed as by the reduction in U.S. consumption divided by the elasticity of oil (the change in demand divided by the change in price).
[958] The decline is petroleum prices caused by lower U.S. demand does have consequences for economic welfare, because it leads to increases in consumer surplus to both domestic and foreign petroleum users. However, lower prices also reduce producer surplus to domestic and overseas suppliers of petroleum, and in total these losses in producer surplus exceed gains in consumer surplus to petroleum users. How domestic economic welfare changes depends on the U.S. petroleum import situation, which as discussed below has changed rapidly in recent years. The agency's analysis of this action does not attempt to estimate the net effect of these changes in domestic consumer and producer surplus. If monopolisitic behavior by large petroleum suppliers raises market prices above competitive levels, any resulting transfer of wealth from U.S. consumers to foreign suppliers (which depends on the volume of oil the U.S. imports) represents an additional financial drain on the U.S. economy. More important, their ability to sustain prices above competitive levels causes a loss in potential U.S. GDP even if the nation imports no oil, and this loss represents a real economic cost that can be mitigated by reducing domestic spending on petroleum products. Because NHTSA's analysis does not model or project the ability of petroleum suppliers like OPEC and Russia to engage in monopolistic behavior, however, we cannot estimate the magnitude of this cost or the reduction that would result from saving fuel.
[959] The U.S. Energy Information Administration (EIA) estimates that the United States exported more total crude oil and petroleum products in September and October of 2019, and expects the United States to continue to be a net exporter. See Short Term Energy Outlook. 2019. Available at: https://www.eia.gov/outlooks/steo/archives/nov19.pdf. (Accessed: Feb. 14, 2024).
[960] In fact, much of that transfer has been reversed, so that reducing global petroleum prices may *lower* revenue to U.S. producers by more than it saves domestic consumers.

Figure 6-5, which is a more detailed version of the previous figure, illustrates this situation. As in Figure 6-4, raising standards shifts the U.S. petroleum demand curve inward from $D_{US,0}$ to $D_{US,1}$ causing an inward shift in global demand for petroleum from $D_{G,0}$ to $D_{G,1}$ and reducing the world oil price from P_0 to P_1. Before the decline in U.S. and global demand, domestic petroleum consumers could have purchased the entire output of U.S producers, $S_{US,0}$ barrels, and the U.S would have on net imported an additional volume $Q_{US,0} – S_{US,0}$ to meet remaining domestic demand. In response to the decline in the global petroleum price, U.S. producers reduced their output to $S_{US,1}$ barrels while foreign producers continued to supply the remainder of domestic demand, or $Q_{US,1} – S_{US,1}$ barrels.

Figure 6-5: Effect of Change in United States to Net Exporter of Petroleum



The decline in the global price of petroleum reduces what are often termed “monopsony” payments by U.S. consumers for the quantity they originally purchased by $(P_1 – P_0)*Q_{US,0}$, or area P_0ghP_1 in Figure 6-5. Of this savings, the part P_0jkP_1 represents a revenue loss to U.S. producers, and the remaining component jghk represents lower revenue received by foreign suppliers for their exports to the United States. From a global standpoint, this is simply a reduction in financial transfers that produces no change in welfare, although from a domestic perspective it does represent a reduced financial drain on the U.S. economy.

As the U.S. supply curve for petroleum has gradually shifted outward, the fraction of payments by U.S. consumers going to U.S. producers (which was $(P_0jkP_1)/(P_1ghP_0)$ before tighter standards reduced U.S. demand gradually increased, while the fraction received by foreign producers ($jghk/P_0ghP_1$) gradually fell. When the U.S. supply curve reached the position shown by the dashed line in Figure 6-5 – indicating that all U.S. petroleum consumption could be supplied via domestic production, all payments by U.S. consumers became revenue to U.S. producers. Consequently, any reduction in their value resulting from declining U.S. demand and the resulting fall in global petroleum prices – the so-called “monopsony effect” of reducing domestic consumption – became a financial transfer occurring entirely within the U.S. economy.[961]

Over most of the period spanned by the agency’s analysis, any decrease in domestic spending for petroleum caused by the effect of lower U.S. fuel consumption and petroleum demand on world oil prices is expected to remain largely or entirely a transfer within the U.S. economy. In the case in which large producers are able to exercise market power to keep global prices for petroleum above competitive levels, this reduction in price

[961] As this occurred, the numerator and denominator of the fraction P_0jkP_1/P_1ghP_0 became identical so the value of this fraction approached 1.0, while the numerator of $jghk/P_0ghP_1$ and the value of that fraction approached zero.

should also increase potential GDP in the U.S. However, the degree to which OPEC and other producers like Russia are able to act as a cartel depends on a variety of economic and political factors and has varied widely over recent history, so there is significant uncertainty over how this will evolve over the horizon that NHTSA models. For these reasons, lower U.S. spending on petroleum products that results from raising standards, reducing U.S. gasoline demand, and the downward pressure it places on global petroleum prices, is *not* included among the economic benefits accounted for in the agency's evaluation of this final rule.

6.2.4.2. Macroeconomic Costs of U.S. Petroleum Consumption

In addition to influencing global demand and prices, U.S. petroleum consumption imposes costs that are unlikely to be reflected in the market price for petroleum, or in the prices paid by consumers of refined products such as gasoline.[962] Higher petroleum consumption imposes external economic costs because it exposes the U.S. economy and domestic consumers to increased risks of rapid increases in prices triggered by global events – which may also disrupt the supply of imported oil – and U.S. consumers of petroleum products are unlikely to take these increased risks into account when deciding how much gasoline or other petroleum products to consume.

Interruptions in oil supplies and sudden increases in oil prices can impose significant economic costs not only by raising the costs of commodities whose production and distribution relies on petroleum, but also because they temporarily reduce the level of output that the U.S. economy can generate (often called "potential GDP"). The magnitude of the resulting reduction in U.S. economic output depends on the oil intensity of the economy, and the extent and duration of increases in prices for petroleum products that result from disruptions to global oil supplies. Of course, it also depends on whether and how rapidly prices return to their pre-disruption levels, which in turn depends partly on the petroleum industry's capacity to respond to localized supply disruptions by increasing production elsewhere. Even if prices for oil return completely to their original levels, however, economic output will be at least *temporarily* reduced from the level that would have been possible with uninterrupted oil supplies and stable prices, so the U.S. economy will bear some transient losses it cannot subsequently recover.

Supply disruptions and price increases caused by global political events tend to occur suddenly and unexpectedly, so they can also force businesses and households to adjust their use of petroleum products more rapidly than if the same price increase occurred gradually. Rapid substitutions between different forms of energy and between energy and other inputs, as well as other changes such as adjusting production levels and downstream prices, can be costly for businesses to make. As with businesses, sudden changes in energy prices and use are also difficult for households to adapt to quickly or smoothly, and being forced to do so may cause at least temporary losses in other consumption.

Interruptions in oil supplies and sudden increases in petroleum prices are both uncertain prospects, so the costs of the disruptions they can cause must be weighted or adjusted by the probability that they will occur, as well as for their uncertain duration. The agency relies on estimated costs of such disruptions that reflect the probabilities that price increases of different magnitudes and durations will occur, as well as the resulting costs of lower U.S. economic output and abrupt adjustments to sharply higher prices. Any *change* in the probabilistic "expected value" of such costs that can be traced to lower U.S. fuel consumption and petroleum demand stemming from increased standards represents an external benefit of adopting them.

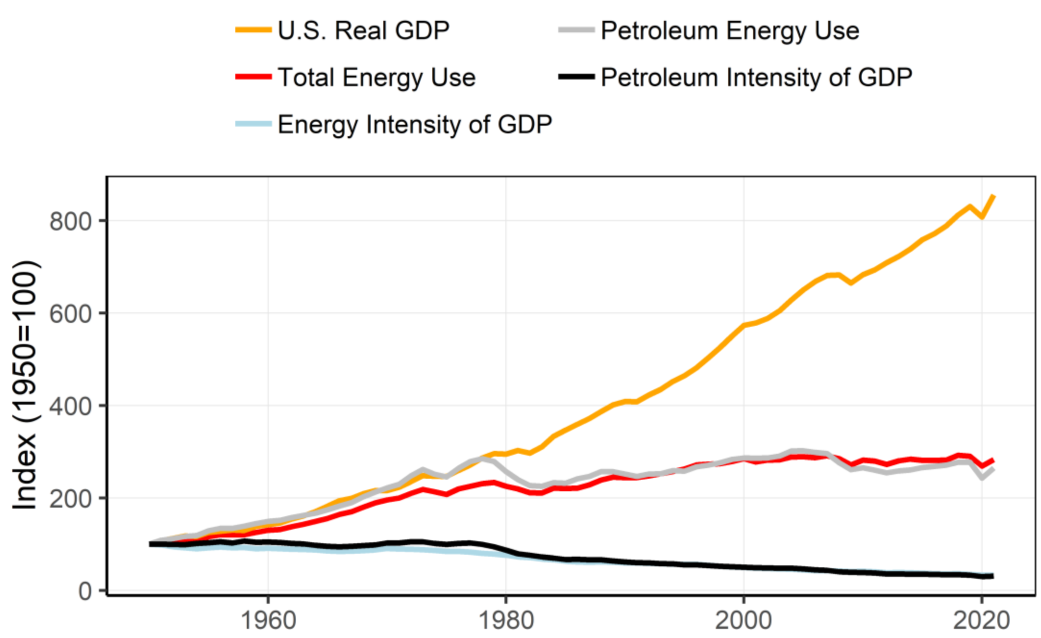
A variety of mechanisms are available to businesses and households to "insure" against sudden increases in petroleum prices and reduce their costs for adjusting to them, and these mechanisms cushion the impacts of sudden price increases. Examples include making purchases or sales in oil futures markets, adopting energy conservation measures, diversifying the fuel economy levels of the different vehicles that households own, locating where public transit provides a viable alternative to driving, and installing technologies that permit rapid fuel switching. Growing reliance on such measures, coupled with continued improvements in energy efficiency throughout the economy, has generally reduced the vulnerability of the U.S. economy to the costs

[962] See, e.g., Bohi, D. R., W. David Montgomery. 1982. Oil Prices, Energy Security, and Import Policy. *Resources for the Future.* Johns Hopkins University Press: Washington, D.C.; Bohi, D. R., Toman, M. A. 1993. Energy and Security - Externalities and Policies. *Energy Policy* Vol. 21: pp. 1093-109; Toman, M. A. 1993. The Economics of Energy Security - Theory, Evidence, Policy. in A. V. Kneese & J. L. Sweeney, eds. 1993. *Handbook of Natural Resource and Energy Economics*. Vol. III: Amsterdam - North-Holland, pp. 1167–218.

of oil shocks in recent decades, and there is now considerable debate about the potential magnitude of economic damages from sudden increases in petroleum prices.

Nevertheless, domestic gasoline prices remain linked to global oil markets, and increased domestic oil production cannot insulate the U.S. economy against price spikes and disruptions originating in the global oil market. Because that linkage remains, reducing the oil-intensity of the U.S. economy by adopting policies such as higher fuel economy and efficiency standards continues to reduce the exposure of U.S. consumers to sudden disruptions and provide real economic benefits by doing so.

Figure 6-6: U.S. Energy Intensity, 1950 – 2021[963]



As with the overall energy intensity of the U.S. economy, the *petroleum* intensity of U.S economic output has also declined significantly over time, while global oil prices have fallen to levels somewhat lower (in real terms) than when analysts first identified and quantified the risks, they create to the U.S. economy. As Figure 6-6 illustrates, U.S. GDP and the nation's consumption of petroleum-based energy grew at almost exactly the same rate from 1950 through 1980, after which petroleum consumption leveled off while GDP continued to grow steadily. Consequently, petroleum energy consumption per dollar of U.S. economic output declined steadily from 1980 through 2020, as the figure shows, and AEO 2023 projects that the petroleum intensity of U.S. GDP will fall by more than 40 percent from its current level over the next three decades. Not only has the United States dramatically increased its own petroleum supply, but other new global suppliers have emerged as well, and both developments reduce the potential impact of disruptions in the unstable or vulnerable regions of the globe that have historically represented the most critical sources of supply.

Therefore, the potential macroeconomic costs of sudden increases in oil prices are now likely to be considerably smaller than when they were originally identified and estimated. Recognizing this situation, the National Research Council (2009) argued that non-environmental externalities associated with dependence on foreign oil are now small, and perhaps trivial.[964] Research by Nordhaus and by Blanchard and Gali (2010) also questioned how harmful more recent oil price shocks have been to the U.S. economy, noting that the

[963] U.S. GDP: U.S. Bureau of Economic Analysis. Real Gross Domestic Product, Quantity Indexes Table 1.1.3. Available at: https://apps.bea.gov/iTable/?reqid=19&step=2&isuri=1&categories=survey#eyJhcHBpZCI6MTksInN0ZXBzIjpbMSwyLDNdLCJkYXRhIjpbWyJjYXRlZ29yaWVzIiwiU3VydmV5Il0sWyJOSVBBX1RhYmxlX0xpc3QiLCIzIl1dfQ==. (Accessed: Feb. 14, 2024); U.S. Petroleum and Energy Consumption: Energy Information Administration, Annual Energy Review, Total Energy, Table 1.3 Energy Consumption by Source. Available at: https://www.eia.gov/totalenergy/data/browser/index.php?tbl=T01.03#/?f=A&start=1949&end=2021&charted=3. (Accessed: Feb. 14, 2024).
[964] National Research Council. 2010. Hidden Costs of Energy - Unpriced Consequences of Energy Production and Use. *The National Academies Press:* Washington, D.C. Available at: https://nap.nationalacademies.org/12794/. (Accessed: Feb. 14, 2024).

U.S. economy actually *expanded* rapidly following recent oil price shocks, and that there was little evidence of higher energy prices being passed through into higher wages or prices.[965]

Since these studies were conducted, the petroleum intensity of the U.S. economy has continued to decline, while domestic energy production has increased in ways and to an extent that experts failed to predict, so that the United States became the world's largest producer in 2018.[966] The U.S. shale oil revolution has established the potential for energy independence and placed downward pressure on prices. Lower oil prices are also a result of sustained reductions in U.S. consumption and global demand resulting from energy efficiency measures, many undertaken in response to previously high oil prices.

Reduced petroleum intensity and higher U.S. production have combined to produce a dramatic decline in U.S. petroleum imports, permitting excess U.S. supply to act as a buffer against artificial or natural restrictions on global petroleum supplies due to military conflicts or natural disasters. In addition, the speed and relatively low incremental cost with which U.S. oil production has increased suggests that both the magnitude and (especially) the duration of future oil price shocks may be limited.

A large-scale attack on Saudi Arabia's Abqaiq processing facility—the world's largest crude oil processing plant—on September 14, 2019, caused what was "the largest single-day [crude oil] price increase in the past decade" ($7-8 per barrel), according to EIA.[967] The Abqaiq facility has the capacity to process 7 million barrels per day, or about 7 percent of global crude oil production capacity. However, only three days after the incident – Saudi Aramco reported that Abqaiq was producing 2 million barrels per day, and its entire output capacity was fully restored by the end of September 2019. Thus, the largest single-day oil price increase in the past decade was largely resolved within a week; assuming that average crude oil prices were approximately $70/barrel in September 2019 (slightly higher than their actual average), an increase of $7/barrel would have represented a 10 percent increase as a result of the Abqaiq attack.

This contrasts sharply with the 1973 Arab oil embargo, which lasted several months and raised prices nearly 350 percent.[968] Saudi Arabia could have taken advantage of increased revenue resulting from higher prices following the Abqaiq attack, but instead moved rapidly to restore production and tap its domestic reserves to control the risk of resulting price increases. In doing so, the Saudis likely recognized that sustained, long-term price increases would reduce their ability to control global supply (and thus to affect global prices and their own revenues) by relying on their lower cost of production.[969]

During the early months following Russia's 2022 invasion of Ukraine, the United States and the European Union (EU) announced plans for embargoes on imports of Russian crude oil. Russia is the world's third largest oil producer, and initial projections anticipated a production decrease of around 1.5-3 mb/d.[970] Initially the Brent spot price for crude oil rose more than 30 percent from pre-invasion levels. While prices remained

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[965] Nordhaus (2007) argues that one reason for limited vulnerability to oil price shocks is that monetary policy has become more accommodating to the price impacts, while another is that U.S. consumers and businesses may determine that such movements are temporary and abstain from passing them on as inflationary price increases in other parts of the economy. He also notes that changes in productivity in response to recent oil price increases have been extremely modest, observing that "energy-price changes have no effect on multifactor productivity and very little effect on labor productivity." at 19. Blanchard and Gali (2010) contend that improvements in monetary policy, more flexible labor markets, and the declining energy intensity of the U.S. economy (combined with an absence of concurrent shocks to the economy from other sources) lessened the impact of oil price shocks after 1980. They find that "the effects of oil price shocks have changed over time, with steadily smaller effects on prices and wages, as well as on output and employment. The message…is thus optimistic in that it suggests a transformation in U.S. institutions has inoculated the economy against the responses that we saw in the past." at 414; See Nordhaus, W. 2007. Who's Afraid of a Big Bad Oil Shock? Available at: https://www.brookings.edu/wp-content/uploads/2007/09/2007b_bpea_nordhaus.pdf. (Accessed: May 31, 2023); Blanchard, O., Gali, J. 2010. The Macroeconomic Effects of Oil price Shocks - Why are the 2000s so Different from the 1970s? in Gali, J., & Gertler, M., eds., *The International Dimensions of Monetary Policy*. University of Chicago Press: Chicago, Il. Feb. 2010. pp. 373–421. Available at: http://www.nber.org/ses/c0517.pdf. (Accessed: Feb. 14, 2024).

[966] EIA. 2019. The U.S. Leads Global Petroleum and Natural Gas Production With Record Growth in 2018. Last revised: Aug. 20, 2019. Available at: https://www.eia.gov/todayinenergy/detail.php?id=40973. (Accessed: Feb. 14, 2024); EIA. 2018. The United States Is Now the Largest Global Crude Oil Producer. Sept. 12, 2018. Available at: https://www.eia.gov/todayinenergy/detail.php?id=37053. (Accessed: Feb. 14, 2024).

[967] EIA. 2019. Saudi Arabia Crude Oil Production Outage Affects Global Crude Oil and Gasoline Prices. Last revised: Sept. 23, 2019. Available at: https://www.eia.gov/todayinenergy/detail.php?id=41413. (Accessed: Feb. 14, 2024).

[968] Whalen, J. 2019. Saudi Arabia's Oil Troubles Don't Rattle the U.S. as They Used to. *Washington Post*. Last revised: Sept. 19, 2019. Available at: https://www.washingtonpost.com/business/2019/09/19/saudi-arabias-oil-troubles-dont-rattle-us-like-they-used. (Accessed: May 31, 2023).

[969] National Petroleum Council. 2019. Dynamic Delivery: America's Evolving Oil and Natural Gas Transportation Infrastructure. p. 18. Available at: https://dynamicdelivery.npc.org/downloads.php. (Accessed: Feb. 14, 2024).

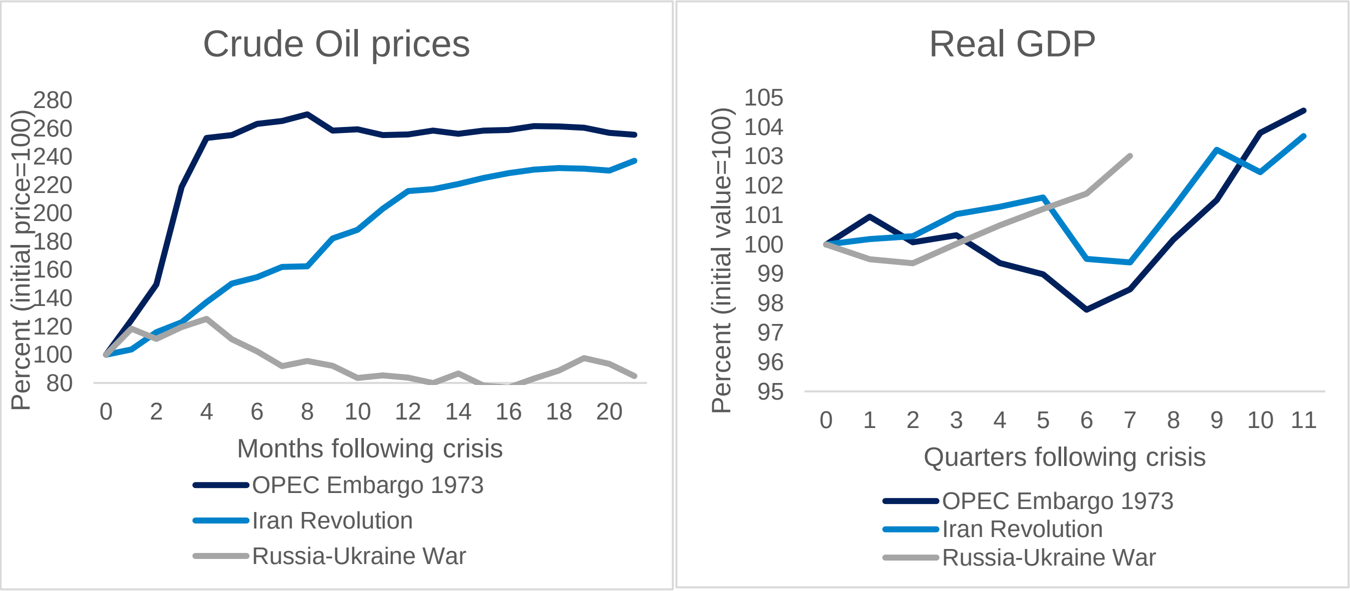
[970] International Energy Agency. 2022. Oil Market Report - April 2022. Oil Market Team. pp. 1-83. Available at: https://www.iea.org/reports/oil-market-report-april-2022. (Accessed: May 31, 2023).

volatile for several months, they eventually stabilized at or below pre-invasion levels by August 2022, less than 6 months after Russia's invasion.

This reversal was caused by several factors including decreased economic activity and demand for oil in China related to COVID-19 restrictions, increased withdrawals from the United States Strategic Petroleum Reserve, and the ability of Russia to maintain production at levels higher than initially anticipated.[971] Even as OPEC has subsequently called for production cuts, increased U.S. production has helped to keep crude oil prices well below their levels at the outset of the invasion. Figure 6-7 shows the crude oil and GDP response in the period following the onset of the Russia-Ukraine War alongside the responses following the 1973 OPEC Embargo and the 1979 Iranian Revolution.[972] Although the recent price response was initially as strong as the response following the OPEC Embargo, it clearly slowed much faster and more dramatically than the price response following those previous shocks.

The macroeconomic response is more complicated, with oil prices, inflation, and supply chain constraints slowing growth more in the initial period following the start of the war. However, while the OPEC Embargo was followed by a prolonged recession, growth returned to pre-war levels during the year following the start of the current war and has continued on an upward trajectory unlike the past shocks. Overall, the macroeconomic implications of this most recent supply shock are still being assessed, yet they already appear far less severe than those stemming from similar previous situations.

Figure 6-7: Impacts of Political Oil Supply Shocks on Crude Oil Price and U.S. GDP[973]



In the initial months following Russia's invasion of Ukraine and the corresponding rise in oil prices, U.S. production of crude oil rose only slightly (around 3 percent), however by September 2022, around 6 months after the invasion, production had increased by 9 percent. Over the first 9 months of 2023 domestic crude oil production averaged levels of around 14 percent higher than 2021, prior to the invasion.[974] The EIA's index of tight oil production (which includes shale) grew by about 16 percent over this same period, reaching 8 million barrels per day through much of 2023.[975] Despite prices moderating since then, domestic production has

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[971] Nagle. 2022. Oil Prices Remain Volatile Amid Demand Pessimism and Constrained Supply. World Bank Blogs. Last revised: Dec. 16, 2022. Available at: https://blogs.worldbank.org/opendata/oil-prices-remain-volatile-amid-demand-pessimism-and-constrained-supply. (Accessed: May 31, 2023).
[972] Gross, S. 2019. What Iran's 1979 Revolution Meant for US and Global Oil Markets. Last revised: Mar. 5, 2019. Available at: https://www.brookings.edu/blog/order-from-chaos/2019/03/05/what-irans-1979-revolution-meant-for-us-and-global-oil-markets/. (Accessed: Feb. 14, 2024).
[973] U.S. Energy Information Administration. Crude Oil Prices Are Taken from the U.S. EIA, Represent U.S. FOB Costs of Crude Oil for OPEC Embargo and Iran Revolution periods, and West Texas Intermediate price for the Russia-Ukraine War. Available at: https://www.eia.gov/petroleum/data.php#prices. (Accessed Feb. 14, 2024).
[974] See U.S. EIA Crude Oil Production. Available at: https://www.eia.gov/dnav/pet/pet_crd_crpdn_adc_mbbl_m.htm. (Accessed: Feb. 14, 2024).
[975] See U.S. EIA Tight Oil Production. Available at: https://www.eia.gov/energyexplained/oil-and-petroleum-products/data/US-tight-oil-production.xlsx. (Accessed: Feb. 14, 2024).

remained more than 10 percent higher than pre-invasion levels and is projected to stay higher through 2024. Thus, while new U.S. oil resources may take some time to respond to supply disruptions, they are nevertheless likely to provide some stabilizing influence on price increases.

Given its lead time, shale is likely to be more effective at mitigating the effects of price increases that occur more slowly. When Beccue and Huntington updated their 2005 estimates of supply disruption probabilities in 2016,[976] they found that the probability distribution had generally "flattened," meaning that supply disruptions of most potential magnitudes were less likely to occur under today's market conditions than they had estimated previously in 2005. Specifically, Beccue and Huntington found that supply disruptions of between two and four million barrels per day were significantly less likely to occur in 2016 than their previous estimates for 2005 had suggested. Although their recent study also estimated that larger supply disruptions (nine or more million barrels per day) are now slightly more likely to occur than in previous estimates, in their view disruptions of this magnitude remain extremely unlikely under either set of estimates.

DOT thus concludes that while shale resources may not be able to stabilize oil markets sufficiently to prevent price increases that originate from rapid, very large supply disruptions elsewhere in the world, U.S. resources are likely to be adequate to stabilize most smaller or less rapid disruptions.

6.2.4.3. Petroleum Imports and U.S. Energy Security

Although the vulnerability of the U.S. economy to oil price shocks depends on the nation's aggregate *consumption* of petroleum rather than on the level of its oil imports, variation in U.S. imports may have some independent effect on the frequency, size, or duration of sudden oil price increases. Insofar as it does, the expected value of potential economic costs from supply or price disruptions would also depend partly on the fraction of U.S. petroleum use that is supplied by imports rather than by domestic production. The estimates of these costs that NHTSA employs in its analysis are expressed as functions of both total U.S. consumption and the share of incremental consumption of petroleum products that is supplied by refining imported oil.

NHTSA estimates these costs separately for domestic and imported oil and converts them to an aggregate per-gallon metric. The agency then applies these costs to fuel consumed using weights derived from the share of petroleum products that are imported in refined form, and to the share of products refined domestically from imported crude petroleum. To support these calculations, NHTSA is required to make specific assumptions about how imports of refined products and crude petroleum are likely to change in response to reductions in consumption of the magnitude expected to result from the standards.

Fuel consumed by the U.S. light-duty vehicle fleet is supplied via three avenues:

1. Importing fuel that has been refined overseas into the United States.
2. Refining fuel within the United States from imported crude petroleum.
3. Refining fuel within the United States from domestically produced crude petroleum.[977]

In its previous rulemaking, the agency reviewed its earlier assumption that 90 percent of any reduction in domestic petroleum refining to produce gasoline that results from the standards would reduce U.S. petroleum imports, with the remaining 10 percent reducing domestic petroleum production. That assumption was based on forecasts of changes in future U.S. fuel consumption and petroleum imports originally published in AEO 2012.

For most of the past half-century, the United States has been a large net importer of crude petroleum, importing the volume necessary to meet the difference between U.S. demand for refined petroleum products and domestic petroleum supply. Throughout this period, the United States has also been largely self-sufficient in refining, meaning that any gap between domestic demand for refined products and the volumes refined from U.S. crude petroleum was primarily met by refining imported crude oil, supplemented only by

[976] Beccue, P. 2016. An Updated Assessment of Oil Market Disruption Risks: Final Report. *Energy Modeling Forum*: Stanford, CA. Stanford University. pp. 1-75. Available at: https://core.ac.uk/download/pdf/211621849.pdf. (Accessed: Feb. 14, 2024).
[977] We assume that all fuel refined outside the United States and then imported into the United States is refined from petroleum that was also produced outside the United States. Although some of it could be refined from crude petroleum produced in the United States and exported, we assume the fraction supplied via this pathway is negligible.

minor imports of refined gasoline. The agency's assumptions about the impacts of conserving fuel on U.S. petroleum imports and refining reflected the expected continuation of this situation.

In the past decade, however, this situation has changed dramatically. U.S. production of crude petroleum has more than doubled since 2008, making the nation one of the world's largest producers, while net imports of crude oil and refined products have declined more than 75-percent.[978] Domestic gasoline consumption declined by more than 6 percent between 2007 and 2012, recovering to its 2007 levels only as recently as 2016, and has remained near or slightly below that level since. Thus, the United States shifted from being a net importer of refined petroleum products to a net exporter in 2011 and has become a net exporter of gasoline and "blending stock" since 2016.[979]

Over the past decade, increased availability of crude petroleum and other refinery feedstocks in combination with declining gasoline consumption has presented U.S. refiners with a choice between continuing to produce gasoline at or near their capacity while boosting exports or cutting back on refinery output. As gasoline consumption declined from 2007 through 2012, U.S. refiners elected not to cut back on their production of gasoline; instead, they *increased* the volume they refined and have continued to do so since 2012 as domestic demand recovered. Overall, refinery and blender production of gasoline increased by 9 percent between 2007 and 2018, while as noted, consumption has only recently recovered to its 2007 level following the COVID-19 pandemic.

The resulting excess of gasoline production over domestic consumption has partly displaced previous gasoline and "blendstock" imports, with the remainder taking the form of increased U.S. exports. As Figure 6-8 shows, the decline in U.S. gasoline consumption after 2007 has not led to a corresponding decline in refinery production, and the nation now has a capacity to produce gasoline that considerably exceeds its current domestic consumption. Further, this surplus of gasoline appears likely to increase in the coming years, as EIA's AEO 2023 reference case (EIA, 2023) anticipates that domestic gasoline consumption will continue to decline until the early 2040s. Barring significant disinvestment in domestic refinery capacity, the United States is thus projected to remain a net exporter of gasoline through the next several decades.

[978] All petroleum statistics are calculated from data at: EIA Petroleum and Other Liquids, Available at: https://www.eia.gov/petroleum/data.php#summary. Net U.S. imports are the difference between the nation's total (or gross) imports from elsewhere in the world and the volumes it exports to other nations.

[979] Another recent change in petroleum markets has been the increasing production and trade in gasoline blendstock in domestic and international petroleum trade. While in earlier periods refineries normally produced finished gasoline and shipped it to local storage terminals for distribution and retailing, in recent years, refineries have increasingly shifted to producing standardized gasoline blendstocks, such as Reformulated Blendstock for Oxygenate Blending (or "RBOB"), which are then shipped and blended with ethanol or other additives to make finished gasoline that meets local regulatory requirements or customer specifications. Although this process has clear cost and operational advantages, particularly with extensive geographic and seasonal variation in gasoline formulations, it complicates the tabulation and comparison of petroleum statistics. In both EIA and most international trade statistics, finished gasoline and blendstocks are treated as separate products, and as reported in EIA statistics, large volumes of finished gasoline are now produced from blendstocks by local "blenders," rather than by more centralized "refiners." In addition, the volume of refinery production of gasoline and blendstock is now systematically lower than consumption of finished gasoline, because up to 10 percent of the volume of gasoline sold at retail can be made up of ethanol that is blended into gasoline after it leaves the refinery.

Figure 6-8: U.S. Gasoline Consumption, Production, and Net Exports: Historical and Forecast[980]

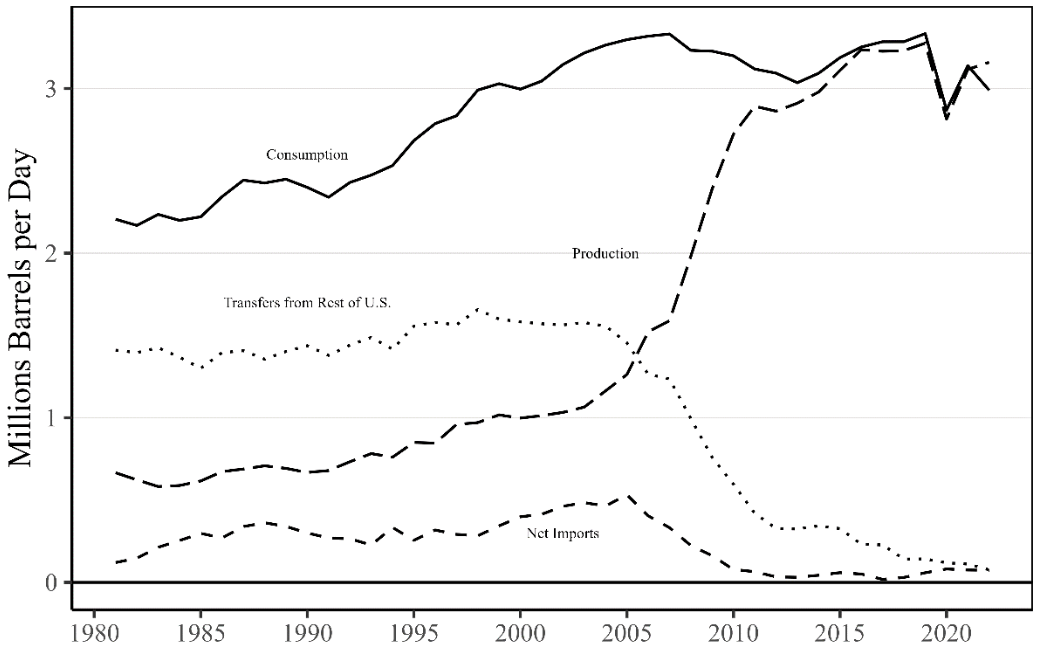
Although EIA's AEO does not include separate forecasts of gasoline exports and imports, that same agency's *Short Term Energy Outlook* projects that U.S. crude and petroleum product net exports will continue to rise through 2024.[981] Taken together, the forecasts of declining U.S. gasoline consumption and rising net exports of refined petroleum products reported in AEO 2023 suggest that that EIA expects the United States to grow as a net exporter of refined petroleum products – including gasoline – through the early 2040s. In turn, this suggests that any decrease in domestic gasoline consumption would be at least somewhat offset by growth in U.S. exports, moderating the resulting decrease in domestic refining and associated upstream emissions.

As Figure 6-9 below shows, during the late 2000s and into the early 2010s gasoline consumption declined, and with it so did imports of gasoline from abroad. In more recent years gasoline production along the East Coast has increased rapidly, while shipments of finished gasoline into the region from the remainder of the United States and imports (mainly from Canada) declined as the gap between consumption and local supply within Petroleum Administration for Defense District (PADD) 1 has closed. This likely reflects increased blending of ethanol with gasoline blendstocks from outside the region as refinery crude oil distillation capacity has declined from over 1.7 million barrels per day in 2009 to under 0.9 million barrels per day in 2024.[982] During that same period motor gasoline blend components from other regions of the US have surged.[983] In June 2019, press reports suggested that that one of the largest East Coast refineries (Philadelphia Energy Solutions, which represents some 28 percent of East Coast refining capacity) would be closed.[984] At the same time, construction of new refineries continues to be hindered by the density of population concentrations and commercial development along the nation's East Coast, casting doubt on the potential for continued increases in local gasoline refining and supply within PADD 1. During the COVID-19 pandemic and the

[980] Historical data are taken from EIA Petroleum and Other Liquids. Available at: https://www.eia.gov/petroleum/data.php#summary. (Accessed: May 31, 2023); Projections are taken from the 2023 AEO Table 11. Petroleum and Other Liquids Supply and Disposition. Available at: https://www.eia.gov/outlooks/aeo/data/browser/#/?id=11-AEO2023&sourcekey=0. (Accessed: Feb. 14, 2024).
[981] EIA. 2023. Short-Term Energy Outlook: Petroleum Products. Last revised: Dec. 12, 2023. Available at: https://www.eia.gov/outlooks/steo/report/petro_prod.php. (Accessed: Feb. 14, 2024).
[982] EIA, East Coast (PADD 1) Operable Crude Oil Distillation Capacity, Available at https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=MOCLEP12&f=A (Accessed: May 23, 2024).
[983] EIA, Movements by Pipeline, Tanker, Barge and Rail between PAD Districts, Available at: https://www.eia.gov/dnav/pet/pet_move_ptb_a_EPOBG_TNR_mbbl_a.htm (Accessed: May 23, 2024).
[984] Seba, E. 2019. Philadelphia Refinery Closing Reverses Two Years of U.S. Capacity Gains. Last revised: Sept. 19, 2019. https://www.reuters.com/article/us-usa-refinery-blast-capacity/philadelphia-refinery-closing-reverses-two-years-of-u-s-capacity-gains-idUSKCN1U0283. (Accessed: Feb. 14, 2024).

period of economic recovery following it, production of finished gasoline in the region moved closely with changes in consumption, while imports and transfers from the rest of the country remained constant.

Figure 6-9: U.S. East Coast (EIA PADD 1) Gasoline Production, Consumption, Transfers from Rest of U.S., and Net Exports[985]

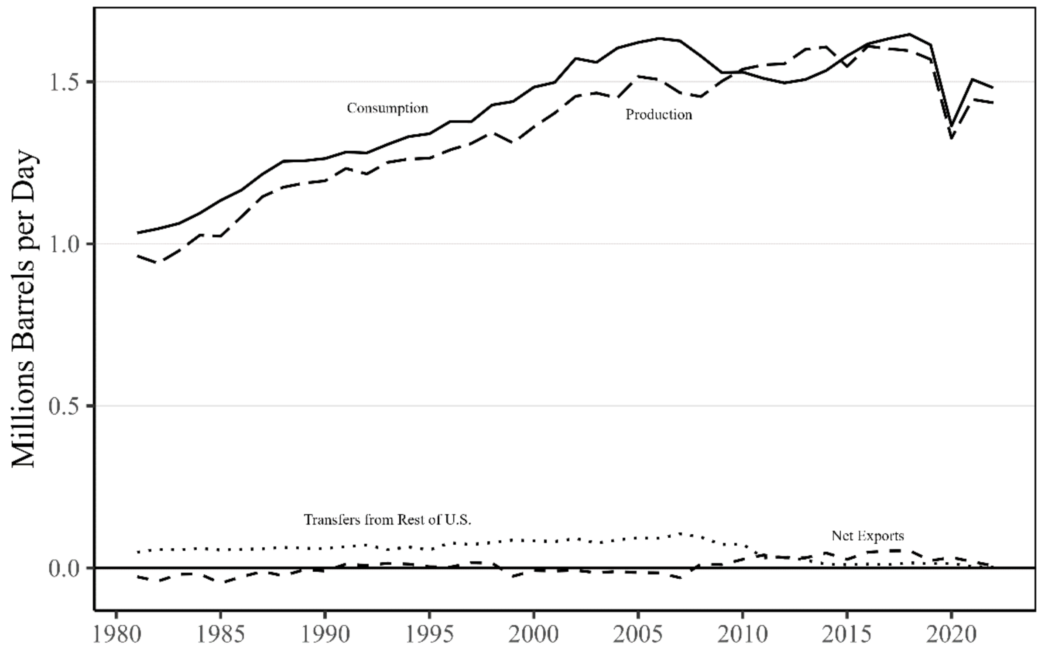


Consequently, it seems likely that any decrease in gasoline consumption along the nation's East Coast likely to result from adopting higher standards would diminish the area's need to rely on foreign imports or on ethanol and other blendstocks from outside the region. Pipelines available to transport refined petroleum products from Gulf Coast refineries to the East Coast may also face capacity limitations, in which case most of any decrease in gasoline consumption there would diminish the need of imports from abroad.

The West Coast, which includes Nevada and Arizona (EIA's PADD 5), currently accounts for 17 percent of U.S. gasoline consumption. Almost all of the gasoline consumed in that region is also refined or blended within it, although small volumes of finished gasoline are shipped into Arizona from neighboring PADDs by pipeline and exported to Latin America by tanker. The West Coast is relatively isolated from other U.S. sources of refined gasoline by long transportation distances and limited pipeline capacity, it appears more likely that reductions in gasoline consumption resulting from adopting higher standards are likely to be met by some combination of reduced refining and increased fuel exports. Figure 6-10 shows that this has been the case in recent decades, as variation in gasoline refining within PADD 5 has closely paralleled that in local consumption, with only modest increases in net exports as consumption has declined recently.

985 EIA 2022. EIA Petroleum and Other Liquids. Last revised: Mar. 7, 2022. Available at: https://www.eia.gov/petroleum/data.php#summary. (Accessed: Feb. 14, 2024).

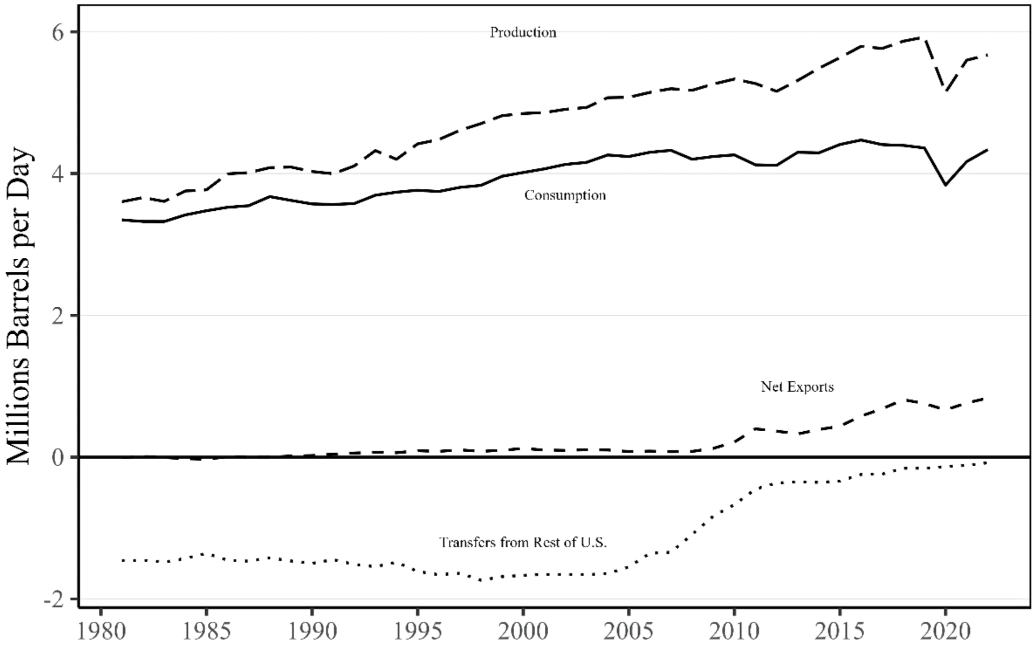
Figure 6-10: U.S. West Coast (EIA PADD 5) Gasoline Production, Consumption, Transfers from Rest of United States, and Net Exports[986]



The central region of the United States (PADDs 2-4) accounts for the remaining 49 percent of U.S. gasoline consumption, and more than half percent of the nation's production of gasoline and blend stock. Although as Figure 6-11 shows the central region on net only exported a minimal quantity of gasoline into the late 2000s, it now exports some 800,000 barrels per day of gasoline and blend stock (primarily to Mexico and other Latin American countries) and has accounted for virtually all of the recent growth in U.S. exports of these two categories of refined products. Recent press reports indicate that firms are currently making significant new investments to add refining capacity on the Gulf Coast to process the growing supply of U.S. shale oil (Douglas, 2019), and with the projected future decline in U.S. consumption, any additional gasoline refined there is likely to increase U.S. exports. Thus, future decreases in gasoline consumption in the central region of the United States of the magnitude likely to result from tightening standards would enable allow additional gasoline exports, even in the absence of additional refinery investments.

[986] EIA 2022. EIA Petroleum and Other Liquids. Last revised: Mar. 7, 2022. Available at: https://www.eia.gov/petroleum/data.php#summary. (Accessed: Feb. 14, 2024).

Figure 6-11: U.S. Central Region (EIA PADDs 2-4) Gasoline Production, Consumption, Transfers from the Rest of United States, and Net Exports[987]



To summarize, based on changes in the various sources of supply that have accompanied recent changes in consumption within different regions of the United States, the agency anticipates that:

- Most of any reduction in gasoline consumption resulting from adopting higher standards that occurs on the East Coast of the United States, which currently accounts for slightly more than one-third of total U.S. consumption, will be met in the near term by reduced transfers of gasoline blend stocks from in other regions of the United States or lower foreign imports of gasoline, and possibly by reduced domestic refining activity over the longer term;
- Most of any decline in U.S. gasoline consumption that occurs on the West Coast, which now accounts for about one-sixth (18 percent) of U.S. gasoline consumption, will be reflected in reduced gasoline refining within that region; and
- Most of any reduction in U.S. gasoline consumption that occurs in the Central region, which currently accounts for nearly half (47 percent) of total U.S. consumption, will be met by increasing exports to foreign markets.

In its proposal, NHTSA assumed that any reduction in fuel consumption would be met with increased exports of refined fuel rather than reduced domestic refining. For the final rule, NHTSA reviewed forecasts of U.S. and global refining activity from McKinsey & Company (2023), S&P Global (2023), and the 2023 AEO, which presented a range of possible outcomes. NHTSA decided that calibrating a simplified model of global market for refined fuel would produce results that could be clearly explained, tested for sensitivity, and adjusted over time as more data becomes available.

Reductions in domestic demand for refined products caused by a change in CAFE standards should be treated as a downward shift in both the US and global long run demand curves for these products. Since these products are bought and sold on international markets, this induces a decrease in the equilibrium price and quantity of the product that depends on the elasticity of global supply. The global supply function represents an aggregation of both American and foreign producers, meaning intuitively that those producers who are most price sensitive, or most elastic will account for a larger share of the reduction in supply. Long

[987] EIA. 2022. EIA Petroleum and Other Liquids. Last revised: Mar. 7, 2022. Available at: https://www.eia.gov/petroleum/data.php#summary. (Accessed: Feb. 14, 2024).

run market dynamics are appropriate in this case since changes to the standards are announced in advance allowing suppliers to anticipate their effect on global demand and adapt their production plans accordingly.

According to its simplified model of the global oil market, NHTSA found that the share of a reduction in domestic consumption that would be reflected in a reduction in domestic refining is equal to the U.S. share of global refining supply, multiplied by the quotient of the U.S. long run price elasticity of refined fuel supply and divided by the elasticity of global refined fuel supply:[988]

Equation 6-11: Calculation of Change in U.S. Refining Activity Relative to Change in Domestic Fuel Consumption

$$\frac{\Delta U.S.\ Refining}{\Delta U.S.\ Consumption} = \frac{\eta_{US}^{R}}{\eta_{W}^{R}} \frac{R_{US}}{R_{W}}$$

For the final rule, NHTSA decided that while long run supply is likely more elastic than short run supply, even in the long run supply is still likely upward sloping with respect to price. NHTSA surveyed the literature for estimates of the appropriate elasticities and was unable to identify suitable estimates for the relative elasticities of U.S. and global supply of refined fuels over the long term. As a result, NHTSA assumed that these supply elasticities would be assumed to be equal for the purpose of this component of the model. The relative price sensitivities of refiners in the U.S. and the rest of the world are determined by relative costs as well as regional demand, both of which are difficult to project over the timeframe of NHTSA's analysis. Since it is possible that the ratio of these elasticities could trend in either direction over the long term, NHTSA's assumption that they are equal is a reasonable approach. Since the U.S. produces about 20 percent of global fuels, NHTSA assumes that for any reduction in petroleum product consumption, domestic refining will decrease by 20 percent of the total consumption reduction. NHTSA explored the sensitivity of its results to this assumption about the relative elasticities of domestic and global supply analyzing cases in which the change in domestic refining as a share of the change in consumption was 0% (perfectly elastic global supply) and 50% (U.S. supply was 2.5 times more elastic than global supply).

Crude oil is a fungible, non-perishable commodity, and can usually be transported among local oil markets around the globe at modest cost; as a consequence, the price of oil in a U.S. domestic market such as Texas is highly correlated with its price in markets located in Northern Europe, the Far East, and the Middle East. In contrast, U.S. gasoline consumption depends on a broad array of factors that overlap only partially with the determinants of U.S. crude petroleum production. These include domestic economic growth and its consequences for transportation demand, current and future vehicle fuel economy, gasoline prices, excise and sales taxes levied on gasoline, pollution standards for fuel, technological and cultural changes, vehicle prices, and the evolution of transportation systems and the built environment.

Recognizing these differences, changes in U.S. consumption and supply of petroleum products seem likely to be reflected primarily in changes in the destination of domestically produced crude petroleum, rather than in its total volume. To the extent that lower U.S. gasoline demand affects domestic refining activity, this is likely to be reflected in larger U.S. exports of crude oil, rather than in a change in U.S. *production* of crude oil. Any changes in U.S. crude oil production would arise primarily from second-order impacts of increased domestic gasoline demand, such as local changes in the relative prices that refiners pay for crude petroleum, or minor changes in global oil prices, and these second-order impacts are in turn likely to have relatively small effects on U.S. petroleum production.

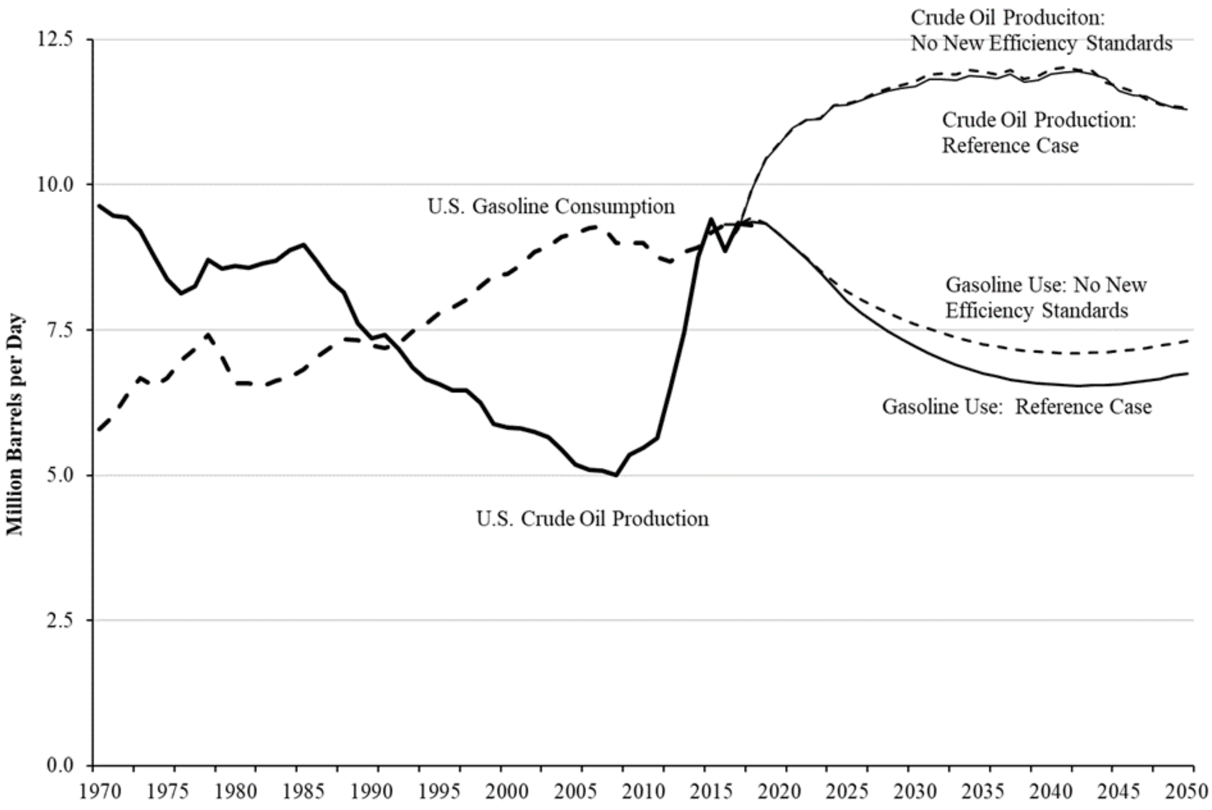
For example, localized and temporary changes in production might arise in response to capacity limitations or transportation bottlenecks associated with particular regions or refineries, temporarily creating a localized market for higher-priced crude oil. However, these situations would normally be localized and prevail for only

[988] NHTSA assumed that the reduction in global consumption is equal to the reduction in domestic consumption caused by a change in CAFE standards. In theory it is possible that the reduction in global prices caused by changes to the standards could induce greater foreign consumption, which would would keep U.S. refining closer to its baseline level. It is also possible that changes to the standards could induce similar technology adoption in the fleets of new vehicles sold in other countries and thus cause a larger decline in global consumption. In this case the change in U.S. refining as a share of the decline in U.S. consumption would be larger.

a limited time.[989] At the same time, the effects of any change in domestic petroleum consumption on world oil prices would be attenuated, because the impact of increased domestic consumption would be felt on prices and volumes supplied in the much larger global petroleum market, rather than confined to the much smaller U.S. market. Any resulting changes in global oil prices and petroleum production would inevitably be small when viewed on a world scale, and likely to prompt only minimal responses in U.S. petroleum supply.

As one indication of the likely minimal impacts of higher U.S. gasoline consumption on U.S. production of crude petroleum, EIA's *AEO 2018* included a side case called "No New Efficiency Requirements," which included a freeze on U.S. fuel economy standards beginning in 2020. Comparing its results to those from the AEO 2018 Reference Case illustrates the insensitivity of domestic crude oil production to changes in domestic gasoline consumption, as represented in EIA's NEMS. Figure 6-12 below presents such a comparison, showing historical trends is U.S gasoline consumption and petroleum production, and comparing their projected future trends in the AEO 2018 Reference Case and No New Efficiency Requirements alternative. As it illustrates, the large increase in U.S. gasoline consumption under the latter scenario relative to the Reference Case is accompanied by an almost indiscernible change in U.S. crude petroleum production, for exactly the reasons described above.

Figure 6-12: Projected U.S. Gasoline Consumption and Crude Oil Production Under AEO 2018 Reference and No New Efficiency Standards Scenario Cases



Sources: EIA, AEO2018 Reference Case and No New Efficiency Standards scenario,and Petroleum Supply Annual, 2019.

Considering the factors that influence U.S. petroleum supply and comparing EIA's forecasts of future changes in domestic petroleum production under very different levels of domestic gasoline consumption, NHTSA believes that in the context of the current global petroleum market, reductions in U.S. gasoline demand on the scale likely to result from adopting any of the alternative increases in standards considered for this final rule

[989] A recent example occurred in May 2021 when a major East Coast oil pipeline owned by Colonial Pipeline was subject to a ransomware attack which raised gasoline prices temporarily in response to regional shortages in the Southeast. Available at: https://www.eia.gov/todayinenergy/detail.php?id=47996. (Accessed: Feb. 14, 2024).

are unlikely to prompt significant changes in domestic petroleum production, and fuel refining. Instead, they are likely to affect mainly the distribution of crude petroleum and gasoline produced within the United States between domestic consumption and U.S. exports to serve global markets, namely by reducing the volumes supplied to U.S. markets and increasing exports. As a consequence, the agency continues to assume that 90 percent of any reduction in domestic consumption of refined fuels leads to increased exports of crude, while only around 10 percent of the reduction is reflected in decreased petroleum production.[990]

6.2.4.4. Estimates of Energy Security Benefits Used to Evaluate the Final Rule

In earlier rulemakings, NHTSA relied on estimates of the external costs from increased petroleum imports and consumption originally prepared by ORNL and updated periodically to reflect changes in oil market conditions. In its more recent model year 2024-2026 Final Rule and model year 2021-2026 Final Rule, however, the agency elected to use estimates reported in a published academic paper by Brown (2018).[991]

In the proposal, NHTSA surveyed recent literature and considered options for updating its estimates of energy security externalities, including using estimates reported in published research or developing new estimates of these externalities based upon methods drawn from the literature. Ultimately the agency decided to produce its own estimates of these externalities using methods described in Brown (2018). For this final rule, NHTSA updated these estimates to reflect changes in projections of oil market conditions between the 2022 AEO and the more recent 2023 AEO. The advantage of developing estimates based on a well-established methodology is that they can be presented transparently and readily updated to reflect future changes in oil market conditions. The sensitivity of these estimates to critical assumptions and input values can also be explored, which allows NHTSA to examine the robustness of its analysis of the effect of changes to the standards.

NHTSA limits its quantification of oil market externalities to the effect of oil supply shocks on expected GDP losses which result from temporarily elevated prices (caused by the short-term inelasticity of oil supply and demand).[992] Sudden or unexpected increases in prices for petroleum products disrupts economic growth and has in the past been followed by economic slowdowns. Reducing domestic petroleum consumption affects the magnitude of these slowdowns through two channels. First, reducing domestic oil consumption lowers the oil intensity of the U.S. economy, making it less sensitive to oil price changes and thus reducing the adjustment costs and temporary losses they impose. Second, when reduced consumption is met by lower imports of oil, the size of the foreign oil supply will decline; this reduces the expected size of any global oil supply disruptions, thus mitigating their expected impact on oil prices. If lower consumption is instead met by reducing domestic oil supply, then the U.S. domestic share of remaining global oil supply decreases, which amplifies the expected price effects of foreign supply shocks.

NHTSA follows the approach outlined in Brown (2018) to calculate the effect of a marginal increase in domestic petroleum consumption on the size of expected GDP losses due to supply shocks. Like Brown, NHTSA's estimates differentiate between the effects of increases in oil imports and domestic production. The agency then combines these estimates using weights consistent with its assumptions regarding the fractions of U.S. petroleum consumption supplied domestically and by oil imports. Both estimates capture the marginal effect of a one-barrel increase in petroleum consumption and are scaled down to a per-gallon basis for use in the agency's CAFE Model, where each gallon of reduced petroleum consumption resulting from the rule averts this estimated per-gallon premium.

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[990] In addition, NHTSA examined differences in crude oil production between "High Economic Growth" and "Low Economic Growth" cases in the 2023 AEO as a ratio of the difference in motor gasoline and diesel consumption between these cases and found a ratio between 10 and 11 percent. AEO 2023 data available can be found in Table 11 Petroleum and Other Liquids Supply and Disposition, Available at: https://www.eia.gov/outlooks/aeo/data/browser/#/?id=11-AEO2023&region=0-0&cases=ref2023&start=2021&end=2050&f=A&sourcekey=0 (Accessed: April 25, 2024).

[991] See Brown, S. 2018. New Estimates of the Security Costs of U.S. Oil Consumption. *Energy Policy*. Vol. 13(2018): pp. 171-92. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0301421517307413. (Accessed: Feb. 14, 2024).

[992] As indicated in the previous subchapter, if large petroleum suppliers are able to exercise market power and sustain global prices above competitive levels, there are additional costs to the U.S. economy beyond these externalities, including transfers of wealth from U.S. consumers to foreign suppliers and reductions in U.S. potential GDP. Because their magnitude depends on the petroleum intensity of U.S. economic activity and the volume of U.S. oil imports, reducing U.S. petroleum consumption by raising CAFE and fuel efficiency standards can also reduce these costs, thus providing additional benefits. Again, the agency's analysis does not attempt to quantify these benefits, because doing so would require estimating the effect of suppliers' market power on the gap between actual petroleum prices and their levels in a more competitive global market, as well as the extent to which lower U.S. petroleum consumption would reduce both market power and this price gap.

Following Brown, NHTSA defines the effect of a petroleum supply shock of magnitude D_i on U.S. GDP, Y_{US}, when the long-run equilibrium world oil price is P_W as:

$$\Delta Y_i = Y_{US} \cdot \left(\frac{P_W + \Delta P_{Wi}(D_i)}{P_W}\right)^{\eta_{GUS}} - Y_{US}$$

Here η_{GUS} is the oil price elasticity of U.S. GDP. This elasticity is negative (because higher prices during a shock are a drag on growth) and its magnitude is directly related to the sensitivity of the entire U.S. economy to oil prices.

To solve for the effect of the supply shock (again, D_i) on the global oil price (P_W), or $\Delta P_{Wi}(D_i)$, NHTSA uses the formula:

$$\Delta P_{Wi} = P_W \left(\frac{Q_W - D_i}{Q_W}\right)^{1/\eta} - P_W$$

Where η is a composite short-run elasticity of global oil prices with respect to changes in global supply, defined as:

$$\eta = (\eta_{DUS} + \eta_{YUS}\eta_{GUS})\frac{QD_{US}}{Q_W} + (\eta_{DROW} + \eta_{YROW}\eta_{GROW})\frac{QD_{ROW}}{Q_W} - \eta_{SUS}\frac{QS_{US}}{Q_W} - \eta_{SROW}\frac{QS_{ROW}}{Q_W}$$

Here we define terms in the same way as Brown (2018): η_{DUS} is the short-run price elasticity of U.S. oil demand, η_{YUS} is the U.S. income elasticity of oil demand, η_{GUS} is the elasticity of U.S. real GDP with respect to oil prices, QD_{US} is the quantity of U.S. oil consumption, η_{DROW} is the short-run price elasticity of foreign (i.e., non-U.S.) oil demand, η_{YROW} is the foreign income elasticity of oil demand, η_{GROW} is the elasticity of foreign real GDP with respect to oil prices, QD_{ROW} is the quantity of foreign oil consumption, η_{SUS} is the short-run price elasticity of U.S. oil supply, QS_{SUS} is U.S. oil production, η_{SROW} is the short-run price elasticity of foreign oil supply, and QS_{ROW} is foreign oil production.

In our estimation procedure the probability distribution of oil supply shocks of varying magnitudes and durations is a discrete probability mass function φ taken from Beccue and Huntington (2016), in line with Brown's approach. NHTSA obtains the expected level of domestic GDP losses due to the possible range of oil supply shocks using the formula:

$$E(\Delta Y) = \sum_{i=0}^{n} \varphi_i \cdot \Delta Y_i(D_i)$$

Here, the changes in GDP from normal oil market conditions during a shock of magnitude D_i are weighted by the probability that such a shock occurs.

Using this approach, NHTSA first estimates the baseline value of $E(\Delta Y)$ under current or projected oil market conditions. The agency then simulates the change in equilibrium oil markets when domestic consumption increases by one barrel of oil and re-calculates a perturbed value, $E(\Delta Y_i')$.[993] Calculations are done separately for the marginal effect of a consumption increase supplied by foreign oil and one supplied by increased domestic production, since their effects on oil market conditions differ. Taking the difference between these quantities and the baseline value yields the corresponding probability-weighted expected effect of the supply disruption on U.S. GDP:

[993] Equilibrium responses include changes in U.S. consumption and production, non-U.S. production, and world price. The equilibrium world price response is determined using long-run elasticities of supply and demand supplied by Brown (2018). The oil price elasticity of U.S. GDP is perturbed by the proportionate change in U.S. oil consumption to GDP when consumption is increased at the margin. If foreign oil production is increased, then the size of oil supply shocks is scaled upwards proportionately to reflect this change.

$$\Delta E(\Delta Y)=\sum_{i=0}^{n}\varphi_i\cdot\left(\Delta Y_i^{'}(D_i)-\Delta Y_i(D_i)\right)$$

NHTSA projects its estimates using oil market and macroeconomic conditions from the 2023 AEO Reference Case. In the 2022 final rule, NHTSA relied on estimates taken from Brown (2018) that utilized only a recent subset of elasticity estimates taken from the literature, arguing that economic responses to oil supply shocks have been generally become more moderate in recent decades, leading to estimates that reflect this diminished response. To avoid missing the uncertainty about how this response will evolve in the future, NHTSA decided to use a wider range of elasticities in developing its estimates for this final rule.[994] While NHTSA only uses its mean estimates in its central analysis, the agency does use the full range of its estimates in its sensitivity analysis.

Table 6-24 reports the estimates of reduced per-barrel external costs from potential oil price shocks this analysis uses to estimate the reduction in the total value of those external costs likely to result from increasing standards, where the reduction in the total value is estimated by multiplying each gallon of reduced petroleum consumption resulting from the rule by this estimated per-gallon premium.[995] These estimates are calculated using the detailed procedure described above and expressed per barrel by which higher standards would reduce U.S. petroleum consumption.

Table 6-24: Expected Cost of Petroleum Price Shocks

Year	Oil Security Premium (2021$/Barrel)[996]	AEO 2023 Reference Case West Texas Intermediate Crude Oil Spot Price (2021$/Barrel)
2022	4.21	89.42
2023	4.13	80.00
2024	4.12	85.02
2025	4.15	79.49
2026	4.20	79.51
2027	4.27	79.77
2028	4.33	80.45
2029	4.40	80.90
2030	4.46	81.31
2031	4.52	81.84
2032	4.58	82.55
2033	4.65	82.95
2034	4.71	83.57
2035	4.77	83.97
2036	4.83	84.71
2037	4.90	85.27

[994] The distribution of elasticities used to develop estimates are taken from the “Combined values” estimates in Table 5 of Brown (2018).
[995] This calculation assumes that reduced petroleum consumption by drivers of the regulated fleet would reduce the estimated external costs in proportion to their consumption.
[996] In order to convert per-barrel costs into per-gallon costs, we make the common assumption (used throughout the analysis) that each barrel of petroleum produces 42 gallons of motor gasoline.

2038	4.97	85.62
2039	5.02	86.12
2040	5.08	86.51
2041	5.14	86.98
2042	5.19	87.41
2043	5.24	87.77
2044	5.29	88.15
2045	5.34	88.47
2046	5.39	89.15
2047	5.43	89.56
2048	5.48	90.20
2049	5.52	90.88
2050	5.56	91.10

Because these estimates are based on separate estimates of the effect of changes in consumption on U.S. oil imports and domestic production, they require the agency to project changes in U.S. petroleum imports that are likely to result from the changes in fuel consumed under the standards (changes in domestic supply represent the difference between those in consumption and imports). As discussed above in Chapter 6.2.4.3, DOT has elected to assume that changes in U.S. petroleum consumption caused by changes to fuel economy and fuel efficiency standards will have only a limited impact on domestic oil production. Thus, 90 percent of any decrease in domestic refined fuel production attributable to higher CAFE standards will be reflected in lower crude oil imports.

6.2.4.5. Potential Effects of Fuel Consumption on Petroleum Imports and U.S. Military Spending

A third potential effect of decreasing U.S. demand for petroleum is to enable reduced U.S. military spending to secure the supply of oil imports from potentially unstable regions of the world and protect against their possible interruption. If a decrease in fuel consumption that results from adopting higher standards enables any military spending that is clearly attributable to protecting flows of imported oil to be scaled back, this reduction in outlays would represent an additional external benefit of NHTSA's action. Such benefits could also include decreased costs to maintain the U.S. Strategic Petroleum Reserve (SPR), because it is intended to cushion the U.S. economy against disruptions in the supply of imported oil or sudden increases in the global price of oil.

Some analysts have argued that U.S. military expenditures are uniquely attributable to securing U.S. supplies of petroleum from unstable regions of the globe – the Middle East, in particular.[997] However, such a perspective appears to confuse those costs with the *marginal* impact of changes in oil consumption of the scale likely to result from this final rule on U.S. military activity and its costs. Incrementally reducing domestic petroleum consumption does not seem likely to significantly decrease military spending to protect those resources and ensure their safe and reliable distribution throughout the world. An analysis by Crane *et al*. reached exactly this conclusion, stating that "our analysis addresses the incremental cost to the defense budget of defending the production and transit of oil. It does not argue that a partial reduction of the U.S. dependence on imported oil would yield a proportional reduction in U.S. spending that is focused on this mission. The effect on military cost from such changes in petroleum use would be minimal."[998]

[997] For example see Securing America's Future Energy (SAFE). 2018. The Military Cost of Defending the Global Oil Supply. Available at: http://secureenergy.org/wp-content/uploads/2020/03/Military-Cost-of-Defending-the-Global-Oil-Supply.-Sep.-18.-2018.pdf.
[998] Crane, K. 2009. Imported Oil and U.S. National Security. The RAND Corporation: Santa Monica, CA. Available at: https://www.rand.org/pubs/monographs/MG838.html. (Accessed: May 31, 2023).

Nevertheless, the cumulative long-term effects of successive reductions in U.S. oil consumption, even if they are individually modest, may include enabling the nation to reduce military spending that is directed toward securing global petroleum supplies. However, there is not likely to be a measurable relationship between the incremental reductions in petroleum consumption of the size likely to result from this final rule and the level of U.S. defense spending that can be uniquely ascribed to protecting global oil supplies.

Eliminating petroleum imports (to both the United States and its national security allies) *entirely* might permit the nation to scale back its military presence in oil-supplying regions of the globe, but only to the extent that maintaining this presence is necessitated solely by specific concerns for oil production and transportation, rather than motivated by broader geopolitical considerations. There is little evidence that U.S. military activity and spending in those regions have varied over history in response to fluctuations in the Nation's oil imports or are likely to do so over the future period spanned by this analysis Figure 6-13 shows that military spending as a share of total U.S. economic activity has gradually declined over the past several decades, and that any temporary—although occasionally major—reversals of this longer-term decline have been closely associated with U.S. foreign policy initiatives or overseas wars.

Figure 6-13: Historical Variation in U.S. Military Spending (Percent of U.S. GDP)

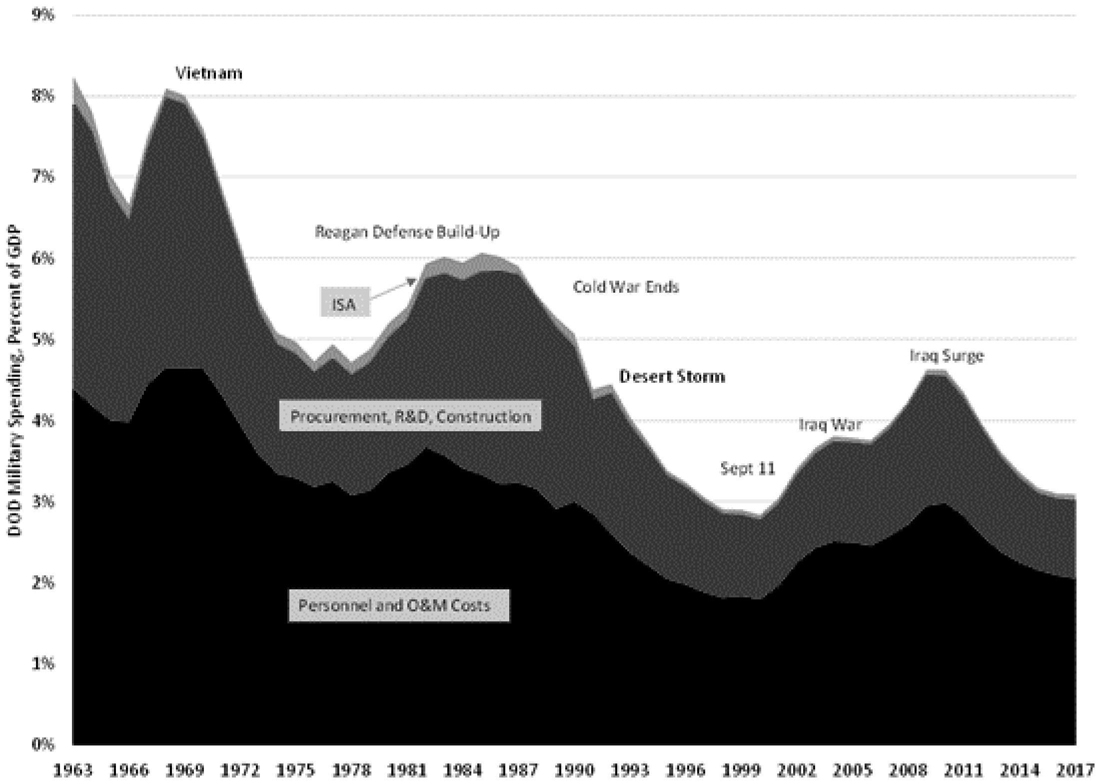
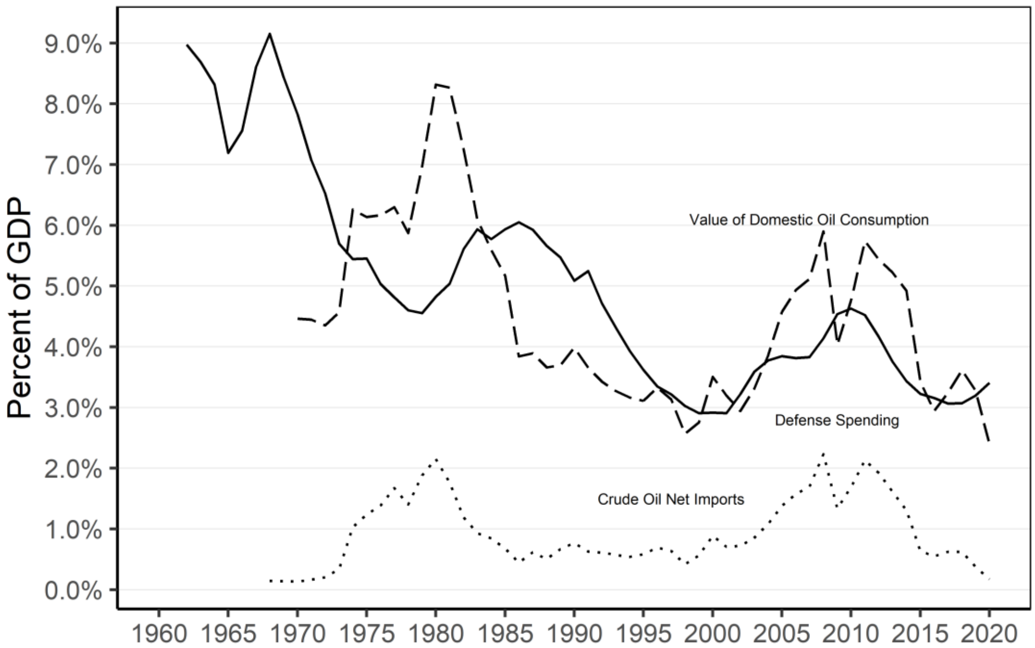


Figure 6-14 superimposes U.S. petroleum consumption and imports on the history of military spending shown in the previous figure. Doing so shows that variation in U.S military spending throughout this period has had little association with the historical pattern of domestic petroleum purchases, changes in which instead primarily reflected the major increases in global petroleum prices that occurred in 1978-79, 2008, and 2012-13. More important, Figure 6-14 also shows that U.S. military spending has often varied independently of the nation's imports of petroleum over most or all this period. Net exports of crude oil have continued their downward trajectory as a share of GDP since 2015 and are projected by AEO to continue to fall over the coming decades; despite this, defense spending has stabilized and risen slightly in recent years. Although this history provides some suggestion that the factors influencing U.S. military activities may include protecting supplies of imported oil, a number of other political and strategic interests limit the degree to which incrementally reducing the nation's consumption of imported petroleum permits military spending to be reduced.

Figure 6-14: Historical Variation in U.S. Military Spending in Relation to U.S. Petroleum Consumption and Imports (Percent of U.S. GDP)



Further, the agency was unable to find any record of the U.S. government attempting to calibrate U.S. military expenditures, force levels, or deployments to any measure of the Nation's petroleum use and the fraction supplied by imports, or to an assessment of the potential economic consequences of hostilities in oil-supplying regions of the world that could disrupt the global market.[999] Instead, changes in U.S. force levels, deployments, and spending in such regions appear to have been governed by purposeful foreign policy initiatives, unforeseen political events, and emerging security threats, rather than by shifts in U.S. oil consumption or imports.[1000] The agency concludes that the degree to which U.S. military activity and expenditures are affected by incremental changes in consumption of petroleum-derived fuels by light-duty vehicle and HDPUVs is uncertain and likely to depend on other national security interests. Over the longer term, successive incremental reductions seem likely to enable *some* reduction in U.S. military activity and spending for the purpose of securing petroleum supplies, but we are unable to find research that calibrates a behavioral relationship between the two. In any event, the resulting benefits are likely to be declining over time as the U.S. economy continues to become less petroleum dependent and the nation remains an oil exporter rather than an importer.

[999] Crane et al. 2009 analyzed reductions in U.S. forces and associated cost savings that could be achieved if oil security were no longer a consideration in military planning and disagree with this assessment. After reviewing recent allocations of budget resources, they concluded that "the United States *does* include the security of oil supplies and global transit of oil as a prominent element in its force planning" at 74 (emphasis added). Nevertheless, their detailed analysis of individual budget categories estimated that even eliminating the protection of foreign oil supplies *completely* as a military mission would reduce the current U.S. defense budget by approximately 12-15 percent. See Crane, K. et al. 2009. Imported Oil and U.S. National Security. The RAND Corporation: Santa Monica, CA. Available at: https://www.rand.org/pubs/monographs/MG838.html. (Accessed: Feb. 14, 2024).

[1000] Crane et al. (2009) also acknowledge the difficulty of reliably allocating U.S. military spending by specific mission or objective, such as protecting foreign oil supplies. Moore et al. (1997) conclude that protecting oil supplies cannot be distinguished reliably from other strategic objectives of U.S. military activity, so that no clearly separable component of military spending to protect oil flows can be identified, and its value is likely to be near zero. Similarly, the U.S. Council on Foreign Relations (2015) takes the view that significant foreign policy missions will remain over the foreseeable future even without any imperative to secure petroleum imports. A dissenting view is that of Stern (2010), who argues that other policy concerns in the Persian Gulf derive from U.S. interests in securing oil supplies, or from other nations' reactions to U.S. policies that attempt to protect its oil supplies. See Crane, K. et al. 2009. Imported Oil and U.S. National Security. The RAND Corporation: Santa Monica, CA. Available at: https://www.rand.org/pubs/monographs/MG838.html. (Accessed: Feb. 14, 2024); Moore, J. et al. 1997. Oil Imports - An Overview and Update of Economic and Security Effects. 1997. Congressional Research Service. *Environment and Natural Resources Policy Division*. Report 98(1): pp. 1-14. Available at: https://www.semanticscholar.org/paper/Oil-Imports%3A-An-Overview-and-Update-of-Economic-and-Moore-Behrens/595d5bee7c3567bc289547fba69f730e32f4b485. (Accessed: May 31, 2023); Council on Foreign Relations. 2015. Automobile Fuel Economy Standards in a Lower-Oil-Price World. Nov. 2015; Stern, R.J. 2010. United States Cost of Military Force Projection in the Persian Gulf, 1976–2007. *Energy Policy.* Vol. 38(6): pp. 2816-25. Available at: https://www.sciencedirect.com/science/article/pii/S0301421510000194?via%3Dihub. (Accessed: Feb. 14, 2024).

Nevertheless, it is possible that more detailed analysis of military spending might identify some relationship to historical variation in U.S. petroleum consumption or imports. A number of studies has attempted to isolate the fraction of total U.S. military spending that is attributable to protecting overseas oil supplies.[1001] These efforts have produced varying estimates of how much it might be reduced if the United States no longer had *any* strategic interest in protecting global oil supplies; however, none has identified an estimate of spending that is likely to vary *incrementally* in response to changes in U.S. petroleum consumption or imports. Nor have any of these studies tracked specific changes in spending that can be attributed to protecting U.S. interests in foreign oil supplies over a prolonged period, so they have been unable to identify whether their estimates of such spending vary in response to fluctuations in domestic petroleum consumption or imports.

NHTSA thus concludes from this review of research that U.S. military commitments in the Persian Gulf and other oil-producing regions of the world contribute to worldwide economic and political stability. Insofar as the costs of these commitments are attributable to petroleum use, however, they are attributable to global oil consumption rather than to U.S. consumption or imports alone. It is thus unlikely that military spending would decline in response to the incremental decrease in U.S. consumption or imports resulting from the standards being finalized here, although the agency acknowledges that the cumulative effect of repeated incremental reductions caused by successive increases in standards may have been to enable lower military spending. Consequently, the agency's evaluation of its final adopted standards assumes that there would be no reduction in government spending to support U.S. military activities in response to the anticipated reduction in gasoline use and U.S. petroleum consumption.

Similarly, while the ideal size of the SPR from the standpoint of its potential stabilizing influence on global oil prices may be related to the level of U.S. petroleum consumption or imports, its actual size has not appeared to vary in response to either of those measures.[1002] The budgetary costs for maintaining the SPR are thus analogous to U.S. military spending, in that while they are not reflected in the market price for oil (and thus do not enter consumers' decisions about how much to use), they do not appear to have varied in response to changes in domestic petroleum consumption or imports. Recognizing these findings, NHTSA's analysis of the final rule does not include any reduction in the cost to maintain a (possibly) smaller SPR as an external benefit of the expected reduction in gasoline and petroleum consumption. This view aligns with the conclusions of most recent studies of military-related costs to protect U.S. oil imports, which generally conclude that savings in military spending are unlikely to result from incremental reductions in U.S. consumption of petroleum products on the scale of those that would resulting from adopting higher standards.

6.2.4.6. Emerging Energy Security Considerations

As discussed above, energy security has traditionally referred to the nation's ability to reliably acquire *petroleum* in sufficient quantities to meet domestic demand (for gasoline, in particular), and to do so at an acceptable cost. However, as the number of electric vehicles on the road continues to increase, the concept of energy security is likely to expand to encompass the United States' ability to supply the materials necessary to build these vehicles and the additional electricity necessary to power their use. While nearly all electricity in the United States is generated through the conversion of domestic energy sources and thus its supply does not raise security concerns, electric vehicles also require batteries to store and deliver that electricity. Currently, the most commonly used vehicle battery chemistries include materials that are either relatively scarce or expensive, are sourced from overseas sites,[1003] and (as with all mined minerals) can pose environmental challenges during extraction and conversion to usable material. It should be noted that these features of the battery material supply chain, including battery chemistry and sourcing origins, supply chains

[1001] These include Copulos, M R. 2003. America's Achilles Heel - The Hidden Costs of Imported Oil. Alexandria VA - The National Defense Council Foundation. pp. 1-153. Available at: https://d35t1syewk4d42.cloudfront.net/file/1595/Americas-Achilles-Heel-The-Hidden-Costs-of-Imported-Oil_NDCF-Copulos_2003.pdf; Copulos, M R. 2007. The Hidden Cost of Imported Oil--An Update. The National Defense Council Foundation. Available at: http://www.ndcf.org/energy/NDCF_Hidden_Cost_2006_summary_paper.pdf. (Accessed: Feb. 14, 2024); Delucchi, M.A., Murphy, J.J. 2008. US Military Expenditures to Protect the Use of Persian Gulf Oil for Motor Vehicles. *Energy Policy.* Vol. 36(6) pp. 2253-64; National Research Council. 2013. Committee on Transitions to Alternative Vehicles and Fuels. Transitions to Alternative Vehicles and Fuels. Available at: https://nap.nationalacademies.org/resource/18264/deps_082043.pdf. (Accessed: Feb. 14, 2024).

[1002] In 2022 the U.S. made by its largest release of oil from the SPR (180 million barrels, about 7 times larger than any previous release), which helped to stabilize global petroleum supplies and prices amid market turmoil following Russia's invasion of Ukraine. The nation's reduced dependence on petroleum and current position as a non-imported were undoubtedly important factors enabling the U.S. to make such a large withdrawal from its SPR.

[1003] Barlock, T.A. et al. Feb.2024. Securing Critical Materials for the U.S. Electric Vehicle Industry. ANL-24/06. Final Report. Available at: https://publications.anl.gov/anlpubs/2024/03/187907.pdf. (Accessed: Apr. 5, 2024).

are changing rapidly[1004]and are projected to continue to shift over time, in part due to investments and incentives from the Infrastructure Investment and Jobs Act as well as the Inflation Reduction Act. NHTSA does not include costs or benefits related to these emerging energy security considerations—or the analogous energy security considerations inherent in internal combustion engine vehicle supply chains—in its analysis for this final rule noting the dynamism in this space and the considerable resources being directed to onshoring and friend-shoring supply chains for the United States more broadly.

Most vehicle electrification is enabled by lithium-ion batteries. Lithium-ion battery global production chains have several phases: sourcing (mining/extraction); processing/refining; battery component manufacturing; cell manufacturing; battery module and pack manufacturing; installation of batteries in an EV; and end-of-life management, including recycling.[1005] Because the origins of lithium-ion battery materials are global, accessing them can pose varying geopolitical challenges.[1006] 2022 data from the Securing Critical Minerals report on the production/sourcing of the four key lithium-ion battery materials is shown in Table 6-25.[1007]

Table 6-25: Lithium-Ion Battery Materials Mining Production and Reserves, 2022

Lithium-ion Battery Material Ores and Concentrates	Countries with Largest Mining Production (share of global total)	U.S. Mining Production (share of global total)	Countries with Largest Reserves
Lithium	Australia (47 percent), Chile (30 percent), China (15 percent), Argentina (5 percent)	1 percent	Chile (36 percent), Australia (24 percent), Argentina (10 percent), China (8 percent), United States (4 percent)
Cobalt	Democratic Republic of Congo (70 percent), Indonesia (5 percent), Russia (5 percent), Australia (3 percent), Canada (2 percent)	Less than 0.5 percent	Democratic Republic of Congo (48 percent), Australia (18 percent), Indonesia (7 percent), Cuba (6 percent), Canada (3 percent)
Graphite (natural)	China (65 percent), Mozambique (13 percent), Madagascar (8 percent), Brazil (7 percent)	0 percent	Turkey (27 percent), Brazil (22 percent), China (16 percent), Madagascar (8 percent), Mozambique (8 percent)
Nickel	Indonesia (49 percent), Philippines (10 percent), Russia (7 percent), New Caledonia[1008] (6 percent), Australia (5 percent)	1 percent	Australia (21 percent), Indonesia (21 percent), Brazil (16 percent), Russia (7 percent), New Caledonia[1009] (7 percent)

Table 6-25 shows mining production and reserves for four key battery materials; after minerals are mined, they must be processed into battery-grade materials. While mining of lithium does not present significant geopolitical risk, especially considering the potential for the United States to become a major global supplier, more than half of global lithium is currently done in China.[1010] Cobalt, a component of NMC batteries, is heavily concentrated in the Democratic Republic of Congo, and more than half of global cobalt production is processed in China. Indonesia is the largest supplier of Class I, battery-grade nickel. China is the single largest processor of Nickel, which is also used extensively in stainless steel production, and much of what is

[1004] See Securing Critical Materials for the U.S. Electric Vehicle Industry: A Landscape Assessment of Domestic and International Supply Chains for Five Key Battery Materials (Technical Report) | OSTI.GOV, Trends in batteries – Global EV Outlook 2023 – Analysis - IEA.
[1005] Scott, S., Ireland, R. 2020. Lithium-Ion Battery Materials for Electric Vehicles and their Global Value Chains. Office of Industries Working Paper ID-068. U.S. International Trade Commission. p. 7. Available at: https://www.usitc.gov/publications/332/working_papers/gvc_overview_scott_ireland_508_final_061120.pdf. (Accessed: Feb. 14, 2024) and in the docket for this rulemaking.
[1006] *Id.* at 8.
[1007] Barlock, T.A. et al. Feb. 2024. Securing Critical Materials for the U.S. Electric Vehicle Industry. ANL-24/06. Final Report. Available at: https://publications.anl.gov/anlpubs/2024/03/187907.pdf. (Accessed: Apr. 5, 2024).
[1008] Overseas Territory of France.
[1009] Overseas Territory of France.
[1010] See for example International Energy Agency. 2023. Global Supply Chains of EV Batteries. p. 27. Available at: https://iea.blob.core.windows.net/assets/4eb8c252-76b1-4710-8f5e-867e751c8dda/GlobalSupplyChainsofEVBatteries.pdf. (Accessed: Feb. 14, 2024).

produced in Indonesia and the Philippines is exported to China for stainless steel manufacturing.[1011] Nickel-based cathodes are the dominant EV battery chemistry today but are projected to partially split market share with LFP batteries in the next decade. Cobalt intensity in cathodes has decreased as battery makers shift towards cathode chemistries with higher nickel content or shift away from cobalt-based chemistries entirely due to high prices and ESG concerns related to cobalt production. The rising market share of LFP batteries offers some relief by shifting demand from nickel, cobalt, and manganese, to iron and phosphorous, which are less expensive and more accessible. Mining and processing of graphite, the dominant material used in anodes, takes place in China, though global mining production is expanding in countries including Tanzania, Mozambique, Canada, and Australia.[1012] As Table 6-26 along with the preceding discussion illustrate, battery materials sourcing poses geopolitical risk; however, the United States is expanding domestic production of minerals and a concerted effort to build a secure supply chain with allies and trade partners is underway. The United States is engaged in a portfolio of international engagements to secure mineral supplies from friendly countries. For example, the United States participates in the Minerals Security Partnership, a collaboration of 13 countries and the European Union to invest in a responsible and secure supply chain for critical minerals.

In all regions, increasing attention is being given to vertical integration in the lithium-ion battery industry from material extraction, mining and refining, battery materials, cell production, battery systems, reuse, and recycling. The United States is lagging in upstream capacity but is expected to be one of the leading producers of lithium worldwide by 2030. Since 2021, over $100 billion of investments have been announced for new or expanded U.S. facilities for recycling and upcycling, materials separation and processing, and battery component manufacturing, all of which provide strong demand signals that can spur upstream investments.[1013, 1014] However, there can be benefits and drawbacks in terms of environmental consequences associated with increased domestic mining, refining, and battery production.

Some instances of delayed or cancelled projects have already emerged as a result of environmental conflict. The proposed development of the Rhyolite Ridge lithium deposits in Nevada, a major deposit in the United States, has been complicated by the discovery of an indigenous species of buckwheat, Tiehm's buckwheat flower. On December 16, 2022, the U.S. Fish and Wildlife Service published a final rule designating Tiehm's buckwheat flower as an endangered species and designating 910 acres of critical habitat on land managed by the Bureau of Land management in Rhyolite Ridge.[1015] In a more recent case, Compass Minerals abandoned a lithium brine project in the Great Salt Lake in Utah due to regulatory risks related to state efforts to protect water resources.[1016]

The United States is one of several industrial countries experiencing (and expected to continue experiencing) increased demand for batter minerals. China and the EU are also major *consumers* of lithium-ion batteries, along with Japan, Korea, and other nations. Deployment of electric vehicles and stationary storage systems are increasing demand for battery minerals globally. Given the expectation of increased demand and potential competition from other countries and other industries, securing sufficient supplies of battery materials to enable large-scale shifts to electrification in the U.S. light-duty vehicle fleet and HDPUV fleet may increasingly call for the development of domestic sources of critical raw materials and production capacity. The agency will continue to monitor these issues going forward and determine whether access to these materials constitutes a new form of energy security for which future analyses must account.

To combat these challenges, President Biden issued an E.O. on "America's Supply Chains," aiming to strengthen the resilience of America's supply chains, including those for automotive batteries.[1017] Reports covering 6 sectors were developed by seven agencies within one year of issuance of the E.O., and outlined

[1011] *Id.* at 9.
[1012] *Id*.
[1013] See U.S. Department of Energy. 2023. Battery Supply Chain Investments. Available at: https://www.energy.gov/investments-american-made-energy. (Accessed: Feb. 14, 2024).
[1014] Barlock, T.A. et al. Feb. 2024. Securing Critical Materials for the U.S. Electric Vehicle Industry. ANL-24/06. Final Report. Available at: https://publications.anl.gov/anlpubs/2024/03/187907.pdf. (Accessed: Apr. 5, 2024).
[1015] Department of the Interior, U.S. Fish and Wildlife Service, Endangered and Threatened Wildlife and Plants. Endangered Species Status and Designation of Critical Habitat for Tiehm's Buckwheat. 87 Fed. Reg. 77368 (Dec. 16, 2022).
[1016] Winslow, B. 2024. Compass Minerals to abandon lithium extraction on Great Salt Lake. Standard-Examiner. Feb 8, 2024, Available at: https://www.standard.net/news/environment/2024/feb/08/compass-minerals-to-abandon-lithium-extraction-on-great-salt-lake/. (Accessed: April 24, 2024).
[1017] E.O. 14017. America's Supply Chains. Feb. 24, 2021. 86 Fed. Reg. 11849 (Mar. 1, 2021).

specific actions for the Federal government and Congress to take.[1018] The Biden-Harris administration also awarded billions of dollars from the Bipartisan Infrastructure Law (BIL) to support projects that develop supplies of battery-grade lithium, graphite, and nickel and invest in other battery related mineral production.[1019] Overall, the BIL appropriates tens of billions of dollars for the purpose of battery manufacturing, recycling, and critical minerals.[1020,1021] This includes about $6 billion in grants administered through the DOE Office of Manufacturing and Energy Supply Chains (MESC) to support active material production, the conversion of facilities for the production of EV components, and battery cell production, among other related activities.[1022]

The Inflation Reduction Act updated the Clean Vehicle Credit to be contingent on mineral and battery sourcing requirements. Qualifying for half ($3,750) of the 30D credit requires that an increasing share of the value of the critical minerals contained in EV batteries be extracted or processed in the U.S. or a country with which the U.S. has a Free Trade Agreement (FTA) or be recycled in North America. This critical mineral value percentage increases from 40% in 2023 to 80% in 2027 and later. Starting in 2025, an EV cannot qualify for the clean vehicle credit if the vehicle's battery contains critical minerals that were extracted, processed, or recycled by a "foreign entity of concern."[1023] The Inflation Reduction Act also included an Advanced Manufacturing Production tax credit that incentivizes certain eligible components, such as electrodes, battery cells, and modules for BEVs, and the processing of critical minerals tax credits on a per unit basis.[1024]

Along these same lines, the IRA also removed the $25 billion cap on the total amount of Advanced Technology Vehicles Manufacturing direct loans.[1025] These loans may be used to expand domestic production of advanced technology vehicles and their components. Finally, it established the Domestic Manufacturing Conversion Grant Program, a $2 billion dollar cost-shared grant program to aid businesses in manufacturing for hybrid, plug-in electric hybrid, plug in electric drive, and hydrogen fuel cell electric vehicles.[1026]

These measures are intended to spur the development of more secure supply chains for critical minerals used in battery production. Over $100 billion dollars of investment have been announced towards domestic battery production in the last two years alone (with $150 billion dollars of investment since 2000).[1027]

The Biden-Harris administration has also sought to improve permitting processes.[1028] This includes reforming mining laws to accelerate the development of domestic supplies of critical minerals while ensuring best practices are followed to minimize conflict and environmental harm.[1029] These priorities also include improving community engagement through identifying community engagement officers for permitting processes, establishing community engagement funds to expand the capacity of local governments, Tribes, or community groups to engage on Federal actions, create national maps of Federal actions being analyzed with an Environmental Impact Statement, and transferring funds to Tribal Nations to enhance engagement in National Historic Preservation Act consultations. In March 2023, the administration also released implementation guidance for permitting provisions in the BIL. This guidance directs agencies to among other things: engage in early and meaningful outreach and communication with Tribal Nations, States, Territories,

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[1018] White House. 2022. Executive Order on America's Supply Chains: A Year of Actions and Progress. National Security Affairs: Washington, D.C. Available at: https://www.whitehouse.gov/wp-content/uploads/2022/02/Capstone-Report-Biden.pdf. (Accessed: May 31, 2023).
[1019] National Energy Technology Laboratory. 2022. Biden-Harris Administration Awards $2.8 Billion to Supercharge U.S. Manufacturing of Batteries for Electric Vehicles and Electric Grid. Last revised: Oct. 24, 2022. Available at: https://netl.doe.gov/node/12160. (Accessed: Feb. 14, 2024).
[1020] Congressional Research Service. Energy and Minerals Provisions in the Infrastructure Investment and Jobs Act (P.L. 117-58). CRS Report R47034. Congressional Research Service. Available at: https://crsreports.conress.gov/product/pdf/R/R47034. (Accessed: Feb. 14, 2024).
[1021] Barlock, T.A. et al. Feb. 2024. Securing Critical Materials for the U.S. Electric Vehicle Industry. ANL-24/06. Final Report. Available at: https://publications.anl.gov/anlpubs/2024/03/187907.pdf. (Accessed: Apr. 5, 2024).
[1022] Gohlke, D. et al. Mar. 2024. Quantification of Commercially Planned Battery Component Supply in North America through 2035. Final Report. ANL-24/14. Available at: https://publications.anl.gov/anlpubs/2024/03/187735.pdf. (Accessed: Apr. 5, 2024).
[1023] PL117-169. Section 13401.
[1024] PL117-169, Section 13502.
[1025] See https://www.energy.gov/lpo/inflation-reduction-act-2022 (Accessed: May 31, 2023).
[1026] See https://www.energy.gov/mesc/domestic-manufacturing-conversion-grants. (Accessed: May 31, 2023).
[1027] Gohlke, D. et al. Mar. 2024. Quantification of Commercially Planned Battery Component Supply in North America through 2035. Final Report. ANL-24/14. Available at: https://publications.anl.gov/anlpubs/2024/03/187735.pdf. (Accessed: Apr. 5, 2024).
[1028] See The White House. 2023. Fact Sheet: Biden-Harris Administration Outlines Priorities for Building America's Infrastructure Faster, Safer and Cleaner. Available at: https://www.whitehouse.gov/briefing-room/statements-releases/2023/05/10/fact-sheet-biden-harris-administration-outlines-priorities-for-building-americas-energy-infrastructure-faster-safer-and-cleaner/. (Accessed: Feb. 14, 2024).
[1029] Barlock, T.A. et al. Feb. 2024. Securing Critical Materials for the U.S. Electric Vehicle Industry. ANL-24/06. Final Report. Available at: https://publications.anl.gov/anlpubs/2024/03/187907.pdf. (Accessed: Apr. 5, 2024).

and Local Communities; improve responsiveness, technical assistance, and support; adequately resource agencies and use the environmental review process to improve environmental and community outcomes.[1030] The administration also tasked the Department of the Interior with leading the Interagency Working Group on Mining Laws, Regulations, and Permitting (IWG), whose final report in 2023 identified 65 "policy measures, regulatory changes, and legislative actions to reduce permitting timelines for exploration and development of domestic minerals on Federal land without sacrificing environmental protection."[1031]

6.2.5. Changes in Labor Utilization

Changes in vehicle prices resulting from technologies added to meet the standards will affect new vehicle sales, which will in turn affect employment associated with those sales. Conversely, production of new technologies used to improve fuel economy and fuel efficiency will create new demand for additional labor. NHTSA's analysis includes estimates of automobile industry employment under each of the regulatory alternatives.

The following subchapters describe the assumptions, data and calculations used to estimate the final rule's impact on labor utilization. Chapter 6.2.5.1 characterizes the baseline and describes the data used to obtain the relevant labor estimates for the CAFE Model inputs. Chapter 6.2.5.2 describes how NHTSA estimates labor within the three employment categories included in the analysis—dealership labor, assembly labor, and labor associated with additional fuel saving technologies. Chapter 6.2.5.2.4 contains a description of the calculations done to integrate the labor estimates into the CAFE Model.

NHTSA believes that all labor costs or cost savings imposed by the standards are subsumed by the costs and benefits estimated elsewhere in the analysis, and therefore NHTSA does not separately monetize the labor impacts discussed in this section in the primary benefits and costs of the standards.

6.2.5.1. Labor Utilization Assumptions and Data Description

The analysis considers the direct labor effects that the CAFE standards have across the automotive sector. The facets of the automotive labor market considered include (1) dealership labor related to new light-duty vehicle unit sales; (2) assembly labor for vehicles, engines, and transmissions related to new vehicle unit sales; and (3) labor related to mandated additional fuel savings technologies, accounting for new vehicle unit sales. The labor utilization analysis is narrow in its focus and does not represent an attempt to quantify the overall labor or economic effects of this rulemaking.

All labor effects are estimated and reported at a national level in person-years, assuming 2,000 hours of labor per person-year.[1032] These labor hours are not converted into monetized values because we assume that the labor costs are included in the new vehicle's purchasing price. The analysis estimates labor effects from the forecasted CAFE Model technology costs and from review of automotive labor for the model year 2022 fleet. NHTSA uses information about the locations of vehicle assembly, engine assembly, and transmission assembly, and the percent of U.S. content of vehicles collected from AALA submissions for each vehicle in the reference fleet.[1033] The analysis assumes the portion of parts that are made in the United States will remain constant for each vehicle as manufacturers add fuel-saving technologies. This should not be misconstrued as a prediction that the percentage of U.S. made parts—and by extension U.S. labor— will remain constant, but rather that the agency does not have a clear basis to project where future productions may shift.

From this foundation, the CAFE Model estimates automotive labor effects after estimating how manufacturers could add fuel economy technologies and then estimating impacts on future sales of passenger cars and light trucks. The agency performs a similar analysis for HDPUVs. The model estimates sales in response to the

[1030] See OMB, FPISC, and CEQ. 2023. Memorandum M-23-14: Implementation Guidance for the Biden-Harris Permitting Action Plan. Available at: https://www.whitehouse.gov/wp-content/uploads/2023/03/M-23-14-Permitting-Action-Plan-Implementation-Guidance_OMB_FPISC_CEQ.pdf. (Accessed: June 9, 2023).
[1031] DOI. 2023. Biden-Harris Administration Report Outlines Reforms Needed to Promote Responsible Mining on Public Lands. Sept. 12, 2023. Available at: https://www.doi.gov/pressreleases/biden-harris-administration-report-outlines-reforms-needed-promote-responsible-mining. (Accessed: April 24, 2024).
[1032] The agencies recognize a few local production facilities may contribute meaningfully to local economies, but the analysis reports only on national effects.
[1033] 49 CFR part 583.

different regulatory alternatives, by considering changes in new vehicle prices and new vehicle fuel economy levels.[1034] As vehicle prices rise and fuel consumption falls, we expect vehicle sales to be affected. For this analysis, we assume that if manufacturers sell fewer vehicles, the manufacturers may need less labor to produce the vehicles and dealers may need less labor to sell the vehicles. However, as manufacturers add equipment to each new vehicle, the industry will require labor resources to develop, sell, and produce additional fuel-saving technologies.[1035] We also account for the possibility that new standards could shift the relative shares of passenger cars and light trucks in the overall fleet (see Chapter 4.2.1.3). Since the production of different vehicles involves different amounts of labor, this shift impacts the quantity of estimated labor. We account for the anticipated changes in vehicle sales, shifts in the mix of passenger cars and light trucks, and the addition of fuel-savings technologies that result from the regulation.

For this analysis, NHTSA assumes that some observations about the production of model year 2022 vehicles will carry forward into the future. While innovation is likely to lead to further efficiency gain in output per worker, for simplicity we assume that assembly labor hours per unit will remain at estimated model year 2022 levels for vehicles, engines, and transmissions, and that the factor between direct assembly labor and parts production labor will remain the same. NHTSA makes these simplifying assumptions for modeling purposes and recognizes that they may not reflect actual automotive practices. When considering shifts from one technology to another, we assume that revenue per employee from suppliers and OEMs will also remain constant, even as manufacturers add fuel-saving technologies and experience cost reductions from learning.

NHTSA has traditionally narrowed its focus on automotive labor because adjacent employment factors and consumer spending factors for other goods and services are uncertain and difficult to predict. We do not consider how direct labor changes may affect the macro economy and potentially change employment in adjacent industries. For instance, we do not consider possible labor changes in vehicle maintenance and repair, nor does it consider changes in labor at retail gas stations. We also do not consider possible labor changes due to raw material production, such as production of aluminum, steel, copper, and lithium, nor does NHTSA consider possible labor impacts due to changes in production of oil and gas, ethanol, and electricity.

Finally, NHTSA makes no assumptions regarding part-time-level of employment in the broader economy and the availability of human resources to fill positions. When the economy is at full employment, a fuel economy regulation is unlikely to have much impact on net overall U.S. employment; instead, labor would primarily be shifted from one sector to another. These shifts in employment impose an opportunity cost on society, as regulation diverts workers from other market-based activities in the economy. In this situation, any effects on net employment are likely to be transitory as workers change jobs (e.g., some workers may need to be retrained or require time to search for new jobs, while short-term labor shortages in some sectors or regions could result in firms bidding up wages to attract workers). On the other hand, if a regulation comes into effect during a period of less-than-full employment, a change in labor demand due to regulation would affect net overall U.S. employment because the labor market is not at full employment. Schmalensee and Stavins point out that net positive employment effects are possible in the near term when the economy is at less than full employment due to the potential hiring of idle labor resources by the regulated sector to meet new requirements (e.g., to install new equipment) and new economic activity in sectors related to the regulated sector longer run.[1036] However, the net effect on employment in the long run is more difficult to predict and will depend on the way in which the related industries respond to regulatory requirements. For that reason, we do not include multiplier effects in the main CAFE Model analysis but instead focus on labor impacts in the most directly affected industries, which would face the most concentrated labor impacts. See “Exploration of alternative labor utilization analysis” in Docket No. NHTSA--2023--0022.

The data used for these calculations include the National Automotive Dealers Association (NADA) annual report,[1037] and AALA reports, which are available on the NHTSA website.[1038] The NADA report includes

[1034] See Chapter 4.2.1.

[1035] For the purposes of this analysis, NHTSA assumes a linear relationship between labor and production volumes.

[1036] Schmalensee, R., Stavins, R. 2011. A Guide to Economic and Policy Analysis of EPA’s Transport Rule. White paper commissioned by Exelon Corporation. Docket EPA-HQ-OAR-2010-0799-0676. Available at: https://obamawhitehouse.archives.gov/sites/default/files/omb/assets/oira_2060/2060_06132011-1.pdf. (Accessed: Feb. 14, 2024).

[1037] Manzi, P. 2021. National Automotive Dealers Association. 2021. NADA Data 2021: Annual Financial Profile of America’s Franchised New-Car Dealerships. Available at: https://www.nada.org/media/4695/download?inline. (Accessed: Feb. 14, 2024).

[1038] NHTSA. 2023. Part 583 American Automobile Labeling Act Reports. Last Revised: 2023. Available at: https://www.nhtsa.gov/part-583-american-automobile-labeling-act-reports. (Accessed: Feb. 14, 2024).

information regarding dealership employment related to new light-duty vehicle sales, which serves as the basis for estimating dealership labor hours. The AALA reports list the PVs labeled with their percent U.S./Canadian parts content, the source of their engine and transmission, and the location of final assembly. These values serve as the basis for estimating final assembly and parts production labor.

6.2.5.2. Estimating Labor for Fuel Economy Technologies, Vehicle Components, Final Assembly, and Retailers

The following subchapters discuss NHTSA's approaches to estimating the individual factors related to dealership labor, final assembly labor and parts production, and fuel economy technology labor.

6.2.5.2.1. Dealership Labor

The labor utilization analysis evaluates dealership labor related to new light-duty vehicle sales and estimates the labor hours per new vehicle sold at dealerships. For the analysis, NHTSA considers changes in dealership labor related to sales, finance, insurance, and management. NHTSA does not include maintenance, repair, and parts department labor,[1039] as their effect on new car sales is expected to be small.

To estimate the labor hours that dealerships spend per new vehicle sold, NHTSA uses data from the NADA annual report, which provides franchise dealer employment by department and function.

We calculate the average labor hours per new vehicle sold by using several values provided in the NADA annual report, including the total number of employees at dealerships, the percentages of employees involved in sales, the percentage of supervisors, new and total sales values, and the number of new vehicles sold in dealerships. We use the data in the annual NADA report regarding NADA employment categories to isolate that information to new sales, and calculate that approximately 17 percent of dealership employees' work relates to new vehicle sales (the remaining approximately 83 percent of work is related to service, parts, and used car sales).[1040] Using these values, we estimate the number of employees involved with new vehicle sales (new vehicle sales jobs in the equation below), either as salespeople or in supervisory positions. Equation 6-12 shows how the final labor hours per vehicle value is calculated.

Equation 6-12: Calculation of Labor Hours per New Vehicle Sold

$$\textit{labor hours per new vehicle sold} = \frac{\textit{annual labor hours*new vehicle sales jobs}}{\textit{new vehicles sold}}$$

Where:
Annual labor hours = hours of labor assumed per employee (2,000)
New vehicle sales jobs = number of employees estimated to be involved with new vehicle sales, in salesperson or supervisory positions
New vehicles sold = total number of new vehicles sold in dealerships

We estimate that on average, dealership employees working on new vehicle sales labor for 27.8 hours per new vehicle sold. This labor hours per new vehicle value can be found in the Market Data Input File. For the CAFE Model's total jobs outputs, dealership labor scales directly with sales. See Chapter 6.2.5.2.4 for further discussion of these outputs.

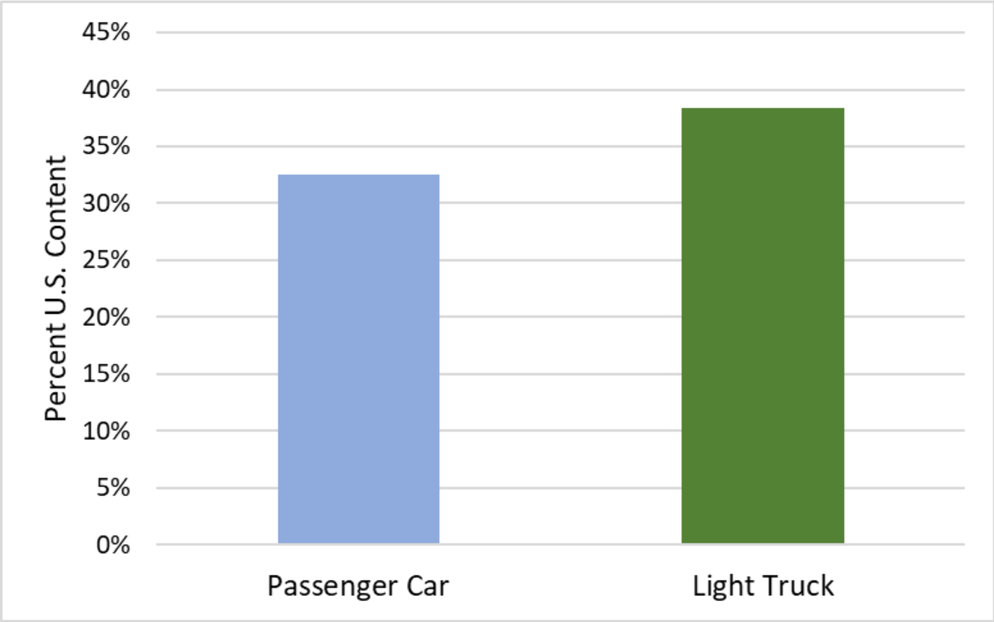
6.2.5.2.2. Final Assembly Labor and Parts Production

As new vehicle sales increase or decrease, the amount of labor required to assemble parts and vehicles changes accordingly. NHTSA evaluates how the quantity of assembly labor and parts production labor will increase or decrease in the future as new vehicle unit sales changes. As a result of the analysis, manufacturing and assembly jobs scale directly with new vehicle unit sales, adjusted for origin of

[1039] These are other labor components reported by the NADA's reports. For instance, a dealership might have a department dedicated to vehicle parts and body shop services.
[1040] Manzi, P. 2021. National Automotive Dealers Association. 2021. NADA Data 2021: Annual Financial Profile of America's Franchised New-Car Dealerships. Available at: https://www.nada.org/media/4695/download?inline. (Accessed: Feb. 14, 2024).

manufacturer. As part of this analysis, NHTSA identifies specific assembly locations for final vehicle assembly, engine assembly, and transmission assembly for each model year 2022 vehicle, to determine the number of assembly labor hours relevant to U.S. employment. In some cases, manufacturers assemble products in more than one location, and the analysis identifies such products and considers parallel production in the labor analysis. For context, Figure 6-15 shows the average percent of U.S. (and Canadian) content, weighted by sales, of passenger cars and light trucks in model year 2022.

Figure 6-15: Sales Weighted Percent U.S. Parts Content by Light-Duty Regulatory Class (MY 2022)



We estimate average direct assembly labor per vehicle (30 hours), per engine (four hours), and per transmission (five hours), based on a sample of U.S. assembly plant employment and production statistics and other publicly available information. NHTSA uses the AALA reports described in Chapter 6.2.5.1 to determine the assembly location of the final vehicle, engine, and transmission.[1041] These reports are grouped generally at the vehicle trim level, with a few exceptions that report variations in percent content within the trim level. The information for HDPUV vehicles in the AALA reports was more limited than for the light-duty sector, but enough information was available to perform a similar exercise for HDPUVs. NHTSA staff were able to leverage data available for select HDPUVs at the model level, some of which was drawn from the previous model year (2021), to use as a proxy. Since Section 583 does not require AALA reporting for all vehicle types within our HDPUV class, we supplement the AALA reports data with readily available vehicle assembly location data that manufacturers make public on their websites.[1042] The HDPUV assembly -hours and percent U.S. content can also be found in the Market Data Input File.

NHTSA uses the assembly locations and the averages for labor per vehicle to estimate U.S. assembly labor hours for each vehicle in the Market Data Input File. U.S. assembly labor hours per vehicle range from as high as 39 hours if the manufacturer assembles the vehicle, engine, and transmission at U.S. plants, to as low as zero hours if the manufacturer imports the vehicle, engine, and transmission. Equation 6-13 shows the

[1041] NHTSA. 2023. Part 583 American Automobile Labeling Act Reports. Last Revised: 2023. Available at: https://www.nhtsa.gov/part-583-american-automobile-labeling-act-reports. (Accessed: Feb. 14, 2024).
[1042] Ford. Worldwide Locations. Available at: https://corporate.ford.com/operations/locations/global-plants/rouge-electric-vehicle-center.html. (Accessed: May 31, 2023); Rivian. 2022. A Tour of the Rivian Plant. Available at: https://stories.rivian.com/vehicle-plant-tour-normal-illinois#:~:text=Rivian%20vehicles%20are%20made%20at,manufacturing%20facility%20in%20Normal%2C%20Illinois. (Accessed: May 31, 2023); Mercedes Benz Group. New Sprinter plant in North Charleston, USA; Mercedes-Benz Vans. Available at https://group.mercedes-benz.com/company/locations/charleston.html. (Accessed: Feb. 14, 2024); Nissan North America Assembly Plants: Smyrna, Decherd and Canton. Available at https://www.nissanusa.com/experience-nissan/news-and-events/where-are-nissans-made.html. (Accessed: Feb. 14, 2024); General Motors. GM Facilities. Available at https://www.gm.com/company/facilities. (Accessed: Feb. 14, 2024); Stellantis Media. 2023. North American Manufacturing Operations. Available at: https://media.stellantisnorthamerica.com/newsrelease.do?id=9117. (Accessed: Feb. 14, 2024).

how NHTSA calculates the U.S. assembly employment hours associated with each vehicle in the Market Data Input File.

Equation 6-13: Calculation of U.S. Assembly Employment Hours

$$\begin{aligned}&\mathit{U.S.\ Assembly\ Employment\ hours}\\&=(\mathit{Vehicle\ Assembly\ location}*30)+(\mathit{Engine\ Assembly\ location}*4)\\&+(\mathit{TransmissionAssemblylocation}*5)\end{aligned}$$

Where:
Vehicle assembly location = Portion of U.S. content, 1 = fully U.S.
Engine assembly location = Portion of U.S. content, 1 = fully U.S.
Transmission assembly location = Portion of U.S. content, 1 = fully U.S.

The analysis also considers labor for parts production. We surveyed motor vehicle and equipment manufacturing labor statistics from the U.S. Census Bureau, the BLS, and other publicly available sources. We found that the historical average ratio of vehicle assembly manufacturing employment to employment for total motor vehicle and equipment manufacturing for new vehicles was roughly constant over the period from 2001 through 2013, at a ratio of 5.26.[1043] Observations from 2001-2013 included many combinations of technologies and technology trends, and many economic conditions, yet the ratio remained about the same over time. Accordingly, we scaled up estimated U.S. assembly labor hours by a factor of 5.26 to consider U.S. parts production labor in addition to assembly labor for each vehicle. The estimates for vehicle assembly labor and parts production labor for each vehicle scaled up or down as unit sales scaled up or down over time in the CAFE Model.

6.2.5.2.3. Fuel Economy Technology Labor

As manufacturers spend additional dollars on fuel-saving technologies, parts suppliers and manufacturers require labor to bring those technologies to market. Manufacturers may add, shift, or replace employees in ways that are difficult for the agency to predict. However, we make a simplifying assumption that revenue per labor hour at OEMs and suppliers will remain about the same as in model year 2022 even as manufacturers include additional fuel-saving technology. To estimate the average revenue per labor hour at OEMs and suppliers, the analysis looked at financial reports from publicly traded automotive businesses. The analysis considers suppliers that won the Automotive New "Pace Award" for innovative manufacturers from 2018-2022, covering more than 40 publicly traded suppliers, NHTSA estimates that OEMs will add one labor year per each $726,489 increment in revenue and that suppliers will add one labor year per $315,807 in revenue.[1044]

NHTSA applies these global estimates to all revenues, and the share of U.S. content is applied as a later adjustment.[1045] NHTSA assumes that these ratios will remain constant for all technologies rather than that the increased labor costs would be shifted toward foreign countries. However, NHTSA acknowledges that this simplifying assumption might not always hold true. For instance, domestic manufacturers may react to increased labor costs by searching for lower-cost labor in other countries, or more labor may be added domestically for fuel efficient vehicles to ensure that they are domestic for the minimum domestic passenger car standard.

The additional labor hours associated with fuel-saving technology are calculated by the CAFE Model based on the values seen in Equation 6-14 and reported as part of the total labor hour outputs (see the Vehicles Report).

[1043] NAICS Code 3361, 3363.
[1044] The analysis assumed incremental OEM revenue as the RPE for technologies, adjusting for changes in sales volume. The analysis assumed incremental supplier revenue as the technology cost for technologies before RPE mark-up, adjusting for changes in sales volume.
[1045] U.S. content information is found in the AALA reports discussed in Chapter 6.2.5.1.

Equation 6-14: Calculation for Fuel Economy Technology Labor Hours

$$\text{Fuel economy tech labor hours} = \left(\frac{\text{Vehicle tech cost}}{\text{OEM revenue}} + \frac{\frac{\text{Vehicle tech cost}}{\text{Supplier revenue}}}{\text{RPE}} \right) * \text{Percent US content} * \text{Annual labor hours}$$

Where:
Fuel economy tech labor hours = labor hours spent on additional fuel-saving technologies (for both OEMs and suppliers)
Vehicle tech cost = cost of technology for each vehicle in the analysis, reported in the CAFE Model outputs
OEM revenue = increment in OEM revenue estimated to correspond to the addition of one labor year
Supplier revenue = increment in supplier revenue estimated to correspond to the addition of one labor year
RPE = revenue per employee
Percent U.S. content = percent of vehicle components built within the United States
Annual labor hours = number of hours assumed to correspond to one labor year

6.2.5.2.4. Labor Calculations in the CAFE Model

NHTSA estimates the total labor effect as the sum of the three components described in the previous chapters: changes to dealership hours, final assembly and parts production, and labor for fuel-economy technologies (at OEMs and suppliers) that are due to the change in CAFE standards. The CAFE Model calculates additional labor hours for each vehicle, based on current vehicle manufacturing locations, simulation outputs for additional technologies, and sales changes. While NHTSA does not consider a multiplier effect of all U.S. automotive-related labor on non-auto related U.S. jobs, the analysis does incorporate a "global multiplier" that can be used to scale up or scale down the total labor hours. We set the value of this parameter at 1.00 (see the Parameters Input File). Equation 6-15, Equation 6-16 and Equation 6-17 illustrate how the CAFE Model calculates base hours (assembly and dealership), innovation hours (associated with additional fuel-saving technology), and total hours, respectively. The labor utilization analysis's final outputs, total U.S. jobs and thousands of labor hours, can be found in the compliance report and the Vehicles Report.

Equation 6-15: Calculation of Base Work Hours per Vehicle

$$\text{Base hours} = (\text{Vehicle U.S. Assembly Hours} * \text{U.S. Assembly Multiplier} + \text{Vehicle Dealership Hours})$$

Equation 6-16: Calculation of Innovation Hours per Vehicle

$$\text{Innovation hours} = \left(\frac{\text{Vehicle tech cost}}{\text{OEM revenue}} + \frac{\frac{\text{Vehicle tech cost}}{\text{Supplier revenue}}}{\text{RPE}} \right) * \text{Percent US content} * \text{Annual labor hours}$$

Equation 6-17: Calculation of Total Labor Hours per Vehicle

$$\text{Total hours} = (\text{Base hours} + \text{Innovation hours}) * \text{Vehicle Sales}$$

Section S5.9 of the CAFE Model Documentation (U.S. Employment) also describes these U.S. labor utilization calculations.

See Chapter 8 of the FRIA for further discussion of the total labor impacts associated with this rulemaking analysis.

7. Safety Impacts of Regulatory Alternatives

The primary objective of CAFE and fuel efficiency standards is to achieve maximum feasible fuel economy and fuel efficiency, thereby reducing fuel consumption. In setting standards to achieve this intended effect, the potential of the standards to affect vehicle safety is also considered. As a safety agency, NHTSA has long considered the potential for safety consequences when establishing standards. Safety consequences include all impacts from motor vehicle crashes, including fatalities, nonfatal injuries, and property damage.

Safety trade-offs associated with increases in fuel economy standards have occurred in the past—particularly before standards became attribute-based—because manufacturers chose to comply with stricter` standards by building smaller and lighter vehicles.[1046] Historically, in cases where fuel economy improvements were achieved through reductions in vehicle size and mass, the smaller, lighter vehicles did not protect their occupants as effectively in crashes as larger, heavier vehicles, on average.[1047] Although NHTSA now uses attribute-based standards, in part to reduce the incentive to downsize vehicles to comply with standards, the agency continues to be mindful of the possibility of safety-related trade-offs.

This safety analysis includes the comprehensive measure of safety impacts from three factors:

1. **Changes in Vehicle Mass**. As with previous analyses, NHTSA analyzes whether there is any safety impact of changes in vehicle mass made to reduce fuel consumption and comply with the standards. Statistical analysis of historical crash data indicates reducing mass in heavier vehicles generally improved safety, while reducing mass in lighter vehicles generally reduced safety. NHTSA's crash simulation modeling of vehicle design concepts for reducing mass revealed similar effects. As discussed below in this analysis, NHTSA's estimates of the effect of changes in mass on safety are not statistically different from zero using confidence levels common in scientific literature.
2. **Impacts of Vehicle Prices on Fleet Turnover**. Vehicles have become safer over time through a combination of new safety regulations and voluntary safety improvements. The agency expects this trend to continue as emerging technologies, such as advanced driver assistance systems (ADAS), are incorporated into new vehicles. Safety improvements will likely continue regardless of changes to the standards.

As discussed in Chapter 4.2, technologies added to comply with fuel economy and fuel efficiency standards have an impact on vehicle prices, therefore slowing the acquisition of newer vehicles and retirement of older ones. A delay in fleet turnover resulting from higher new vehicle prices affects safety by slowing the penetration of new safety technologies into the fleet. The standards also influence the composition of the light-duty and HDPUV fleets. As the safety provided by light trucks, SUVs, passenger cars, and HDPUVs responds differently to technology that manufacturers employ to meet the standards—particularly mass reduction—fleets with different compositions of body styles will have varying numbers of fatalities, so changing the share of each type of light-duty and HDPUV vehicles in the projected future fleet impacts safety outcomes.

3. **Increased driving because of better fuel economy.** The "rebound effect" predicts consumers will drive more when the cost of driving declines. More stringent standards reduce vehicle operating costs, and in response, some consumers may choose to drive more. Additional driving increases exposure to risks associated with motor vehicle travel, and this added exposure translates into higher fatalities and injuries.

1046 NHTSA. 2023. Part 583 American Automobile Labeling Act Reports. Available at: https://www.nhtsa.gov/part-583-american-automobile-labeling-act-reports. (Accessed: Feb, 16, 2024).

1047 Ford. Worldwide Locations. Available at: https://corporate.ford.com/operations/locations/global-plants/rouge-electric-vehicle-center.html. (Accessed: Feb, 16, 2024); Rivian. 2022. A Tour of the Rivian Plant. Available at: https://stories.rivian.com/vehicle-plant-tour-normal-illinois#:~:text=Rivian%20vehicles%20are%20made%20at,manufacturing%20facility%20in%20Normal%2C%20Illinois. (Accessed: Feb, 16, 2024); Mercedes Benz Group. New Sprinter plant in North Charleston, USA; Mercedes-Benz Vans. Available at: https://group.mercedes-benz.com/company/locations/charleston.html. (Accessed: Feb, 16, 2024); Nissan North America Assembly Plants: Smyrna, Decherd and Canton. Available at https://www.nissanusa.com/experience-nissan/news-and-events/where-are-nissans-made.html. (Accessed: Feb, 16, 2024); General Motors. GM Facilities. Available at https://www.gm.com/company/facilities. (Accessed: Feb, 16, 2024); Stellantis Media. 2023. North American Manufacturing Operations. Available at: https://media.stellantisnorthamerica.com/newsrelease.do?id=9117. (Accessed: Feb, 16, 2024).

The contributions of the three factors described above generate the differences in safety outcomes among regulatory alternatives. The agency's analysis makes extensive efforts to allocate the differences in safety outcomes between the three factors. Fatalities, injuries, and property damage-only (PDO) crashes expected during future years under each alternative are projected by deriving a fleet-wide fatality rate (fatalities per vehicle mile of travel) that incorporates the effects of differences in each of the three factors from baseline conditions and multiplying it by that alternative's expected VMT. Fatalities, injuries, and PDO crashes are converted into a societal cost by multiplying fatalities with the DOT-recommended VSL supplemented by economic impacts that are external to VSL measurements. Traffic injuries and property damage are also modeled directly using the same process and valued using costs that are specific to each injury severity level.

Only two of the factors—changes in vehicle mass and in the composition of the light-duty and HDPUV fleets in response to changes in vehicle prices—impose increased risks on drivers and passengers that are not compensated for by accompanying benefits. In contrast, increased driving associated with the rebound effect is a consumer choice that reveals the benefit of additional travel. Consumers who choose to drive more have apparently concluded that the utility of additional driving exceeds the additional costs for doing so including the crash risk that they perceive additional driving involves. As discussed in Chapter 7.5, the benefits of rebound driving are accounted for by offsetting a portion of the added safety costs.

The agency measures safety outcomes using three measures of light-duty and HDPUV vehicle safety: fatalities to vehicle occupants and non-occupants (pedestrians, cyclists, and others) occurring in crashes, serious injuries sustained by occupants and non-occupants, and the number of vehicles involved in crashes that cause property damage but no injuries. Counts of fatalities to vehicle occupants and non-occupants involved in crashes with those vehicles are obtained from NHTSA's Fatal Accident Reporting System (FARS). Estimates of the number of serious injuries to occupants of light-duty and HDPUV vehicles and non-occupants involved in crashes with them are tabulated from NHTSA's General Estimates System (GES) for 1990-2015, and from its Crash Report Sampling System (CRSS) for 2016-2019. Both GES and CRSS include annual samples of motor vehicle crashes occurring throughout the United States. Weights for different types of crashes were used to expand the samples of each type to estimates of the total number of crashes occurring during each year. Finally, estimates of the number of automobiles involved in PDO crashes each year were also developed using GES and CRSS.

The following subchapters discuss the methods used to determine the safety impacts of higher CAFE standards on vehicle occupants and their value to society. The resulting estimates of safety impacts are generated inside the CAFE Model and are detailed in Chapter 5 of the FRIA accompanying this final rule.

7.1. Projecting Future Fatalities and the Safety Baseline

To estimate the effect of imposing higher standards can alter safety, the agency begins by using statistical models that incorporate variation in the safety performance of individual vehicle model years to project future safety outcomes. The agency has developed separate models for fatalities, non-fatal injuries, and property damage to vehicles, each of which tracks model year cohorts of vehicles beginning when they are produced, sold, and enter the fleet; as they gradually age and accumulate usage (and for most vehicles, change in ownership as they age); and are ultimately retired from service. We also consider how introducing newer technologies are likely to affect the safety of individual vehicles, the combined fleet, and other road users such as pedestrians and cyclists.

The overall safety of the light-duty and HDPUV vehicle fleets during any future calendar year is determined by the safety performance of the individual model year cohorts comprising it, the ages they will have reached during that year, the representation of each model year cohort in that year's fleet, and a host of external factors that evolve or fluctuate over time, such as driver demographics and behavior, economic conditions, traffic levels, and improvements in emergency response and medical care. Combining forecasts of future crash rates for individual model year cohorts at different ages with the composition of the vehicle fleet produces a baseline forecasts of fatalities, non-fatal injuries, and vehicles sustaining property damage. Regulatory alternatives that establish new CAFE standards for future model years change these forecasts by altering the representation of different model year cohorts making up the future light-duty and HDPUV fleets.

7.1.1. Historical Trends

The relationships among vehicle age, model year, and safety risks to occupants and pedestrians are significant, and have persisted over time. In a 2020 Research Note, NHTSA's National Center for Statistics and Analysis (NCSA) concluded that an occupant of a 7- to 11-year-old vehicle is 11 percent more likely to be severely injured in a crash than the driver of a vehicle 1-6 years old, after accounting for the vehicle's model year and various factors related to the severity of the crash. The increase in risk is even more pronounced for the oldest vehicles in use, with occupants of vehicles 15 years or older being 23 percent more likely to be severely injured in crashes than occupants of new vehicles (again after controlling for the model years of vehicles involved in crashes).

Despite a recent increase in overall roadway deaths, fatalities and serious injuries suffered by light-duty vehicle and HDPUV occupants as well as by other road uses involved in crashes with them (mainly pedestrians and cyclists) have declined gradually for several decades. New vehicles have become consistently safer over time, most likely because they incorporate advances in safety technology such as side-impact airbags, electronic stability control, and (more recently) the sophisticated crash avoidance systems now featured by an increasing proportion of new vehicles. NHTSA's 2020 study showed that occupants of cars and light trucks produced in model years 1995-2011 were 15 percent more likely to sustain serious injuries in crashes than were occupants of vehicles from more recent model years (2012-18), and that occupants of pre-1987 cars and light trucks were 50 percent more likely to be seriously injured in crashes than occupants of vehicles from the most recent model years. These results account for the model years of vehicles involved in crashes and illustrate that the relationship between vehicles' age and the increased safety risks they pose to occupants and others when they are involved in crashes has persisted as new vehicles have become safer.

7.1.2. Model Framework

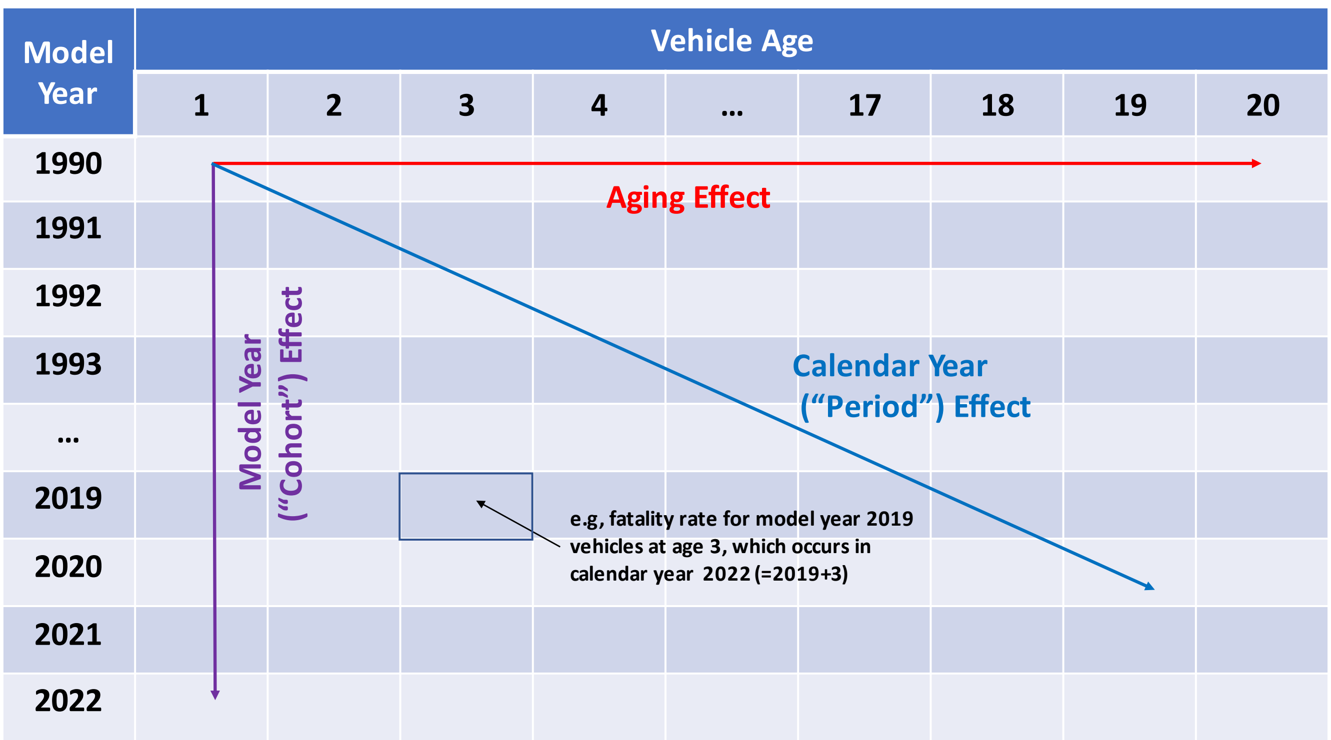
The agency's safety models use an "age-period-cohort" framework, where vehicles produced during a single model year – sometimes referred to as "vintages" – represent the cohorts making up the vehicle fleet or population. The safety performance of each new model year cohort differs from its predecessors, as successive model years entering the fleet have generally become safer over time due to improvements in their design, increased durability resulting from changes in materials and manufacturing methods, the agency's safety regulations, and voluntary adoption of safety-improving features. In addition, the safety performance of each individual model year cohort evolves as it ages, accumulates use, and the vehicles remaining in use are acquired by new owners. The "age- period-cohort" approach disaggregates the evolution of fleet-wide safety improvements into improvements in the safety of new vehicles, the evolution of each model year's safety performance as it ages, and the influence of driver behavior (such as seat and shoulder belt use) and other factors (for example, overall economic conditions) that vary over time in ways that affect the safety of all model years in the fleet.[1048]

The safety performance of individual model-year cohorts tends to follow a common pattern as they age, accumulate use, and for most vehicles, experience changes in ownership and locations where they are driven.[1049,1050] Historically, vehicles' safety appears to deteriorate gradually through approximately age 20, level off for some period, and in rare cases improve thereafter. The causes of this pattern are not completely understood, but the agency suspects that the major factors contributing to the decline in safety through age 20 are their purchase and use by habitually riskier drivers and shifts in where they are driven toward areas where road conditions are less safe and travel speeds higher.

[1048] NAICS Code 3361, 3363.
[1049] The analysis considered suppliers that won the Automotive News "PACE Award" from 2013-2017, covering more than 40 suppliers, more than 30 of which are publicly traded companies. Automotive News gives "PACE Awards" to innovative manufacturers, with most recent winners earning awards for new fuel-savings technologies. The analysis assumed incremental OEM revenue as the RPE for technologies, adjusting for changes in sales volume. The analysis assumed incremental supplier revenue as the technology cost for technologies before RPE mark-up, adjusting for changes in sales volume.
[1050] U.S. content information is found in the AALA reports discussed in Chapter 6.2.5.1. Eun, S. 2020. Trends in Mortality from Road Traffic Injuries in South Korea, 1983–2017: Joinpoint Regression and Age-Period-Cohort Analyses. *Accident Analysis and Prevention.* Vol. 134: pp. 1- 7. Available at: https://doi.org/10.1016/j.aap.2019.105325. (Accessed: May 31, 2023); Langley, J. et al. 2013. Age, Period and Cohort Effects on the Incidence of Motorcyclist Casualties in Traffic Crashes. *Injury Prevention*. Vol. 19(3): pp. 153–57. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3664376/. (Accessed: May 31, 2023).

Figure 7-1 illustrates the age-period-cohort framework as applied to the safety of vehicle travel. New model years introduced into the fleet have generally become progressively safer, and these improvements tend to persist throughout their lifetimes in the fleet, which represents a cohort effect. Vehicles also tend to gradually be involved in more frequent and dangerous accidents as they age and accumulate use, and this effect – which is surprisingly consistent across successive model years – represents an aging effect. Finally, changes in driver demographics and driving behavior, as well as external events such as gradual improvements in emergency crash response or transient periods of economic stress can affect the safety performance of the entire driver population and vehicle fleet. Such time-varying factors–the period effects in age-period-cohort analysis–influence safety independently of and in addition to the effects of safer new vehicles entering the fleet and their gradual aging. As the figure suggests, these three effects are conceptually independent, but interact in ways that combine to produce observed historical evolution in the overall safety of the vehicle fleet.

Figure 7-1: Age, Cohort, and Period Effects on Safety of Vehicle Fleet



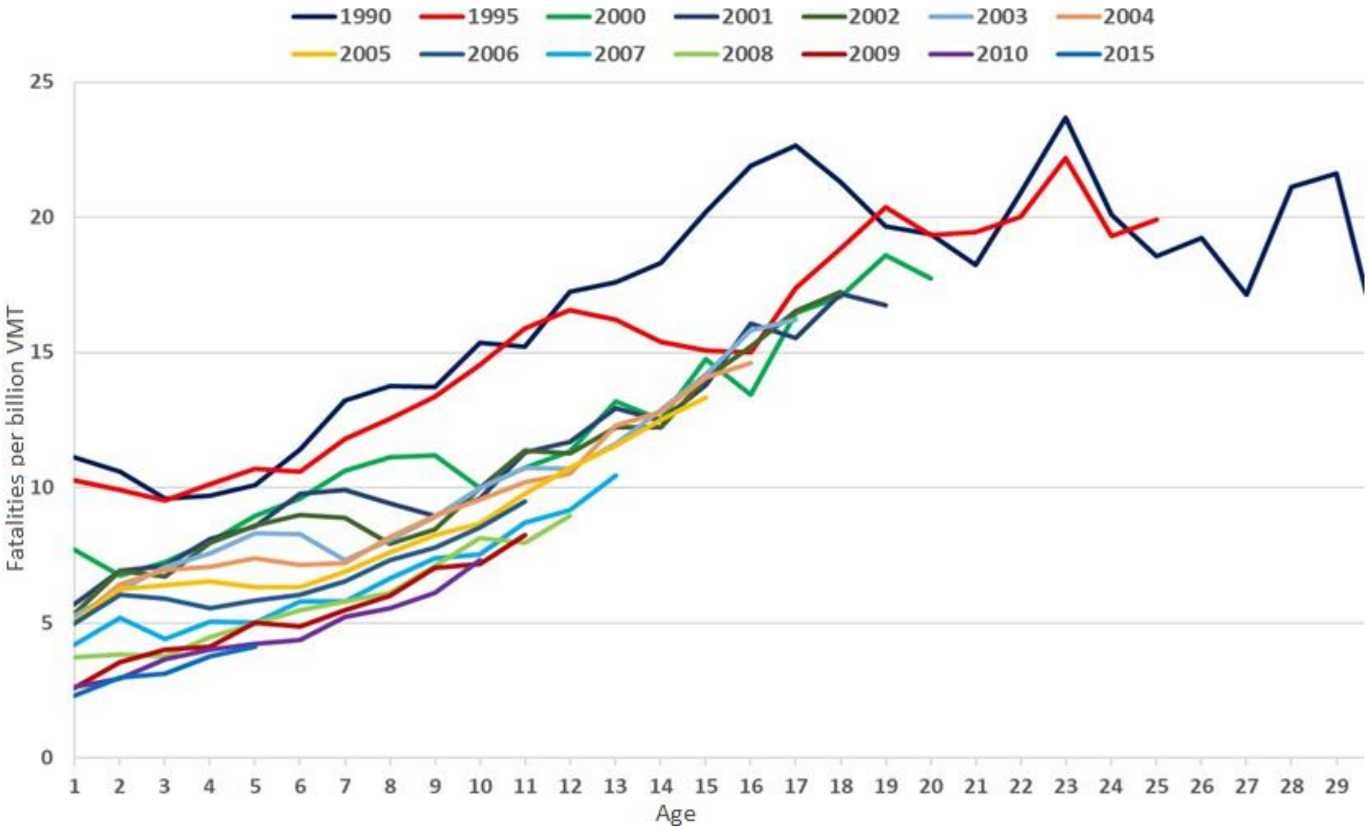
7.1.3. The Aging Effect

Figure 7-2 illustrates changes in the safety performance of selected recent model years of cars and light trucks as each model year cohort ages, using fatalities per billion miles driven as a measure of safety.[1051] It shows a pattern of gradually increasing fatality rates through approximately age 20, after which fatality rates level off, and for some model years ultimately decline. Again, the increase in fatality rates is generally thought to result from transferring ownership of used vehicles to riskier drivers and driving locations, although

[1051] Fatalities occurring among occupants of vehicles of different model years in use during each calendar year, as well as among non-vehicle occupants (mainly pedestrians and cyclists) involved in crashes with them, were tabulated from NHTSA's Fatal Accident Reporting System (FARS, https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars. (Accessed: Feb, 16, 2024). Fatalities among non-vehicle occupants occurring in crashes involving vehicles of different model years were pro-rated among vehicles on the basis of fatalities to vehicle occupants themselves. Fatality rates for each model year and age were then estimated by calculating age as equal to (calendar year – model year) and dividing the count of fatalities for each model year and age by the number of milesvehicles produced during that model year and remaining in use during that calendar year are estimated to be driven. The numbers of non-fatal injuries and vehicles involved in property damage-only crashes were tabulated from NHTSA's National Automotive Sampling System General Estimates System (NASS GES, https://www.nhtsa.gov/national-automotive-sampling-system/nass-general-estimates-system. (Accessed: Feb, 16, 2024)), and were converted to rates per billion miles driven using the same procedure for calculating fatality rates. Again, non-fatal injuries to non-occupants occurring in crashes theat involved vehicles of different model years were assigned on the basis of those to vehicle occupants. Non-fatal injury and property damage only crash rates show patterns of variation over historical model years and age that are similar to those for fatalities shown in Figure 7-2.

structural fatigue with increased usage and resulting mechanical failures also play some small role in explaining the increase.[1052] The decline in fatality rates for some very old vehicles may result because the small share of vehicles that remain in use beyond ages 20-25 tend to be owned by their original purchasers, carefully maintained, and driven on a limited basis under relatively safe conditions.

Figure 7-2: Fatality Rates by Age for Selected Model Years



7.1.4. Safer New Cars: The Cohort Effect

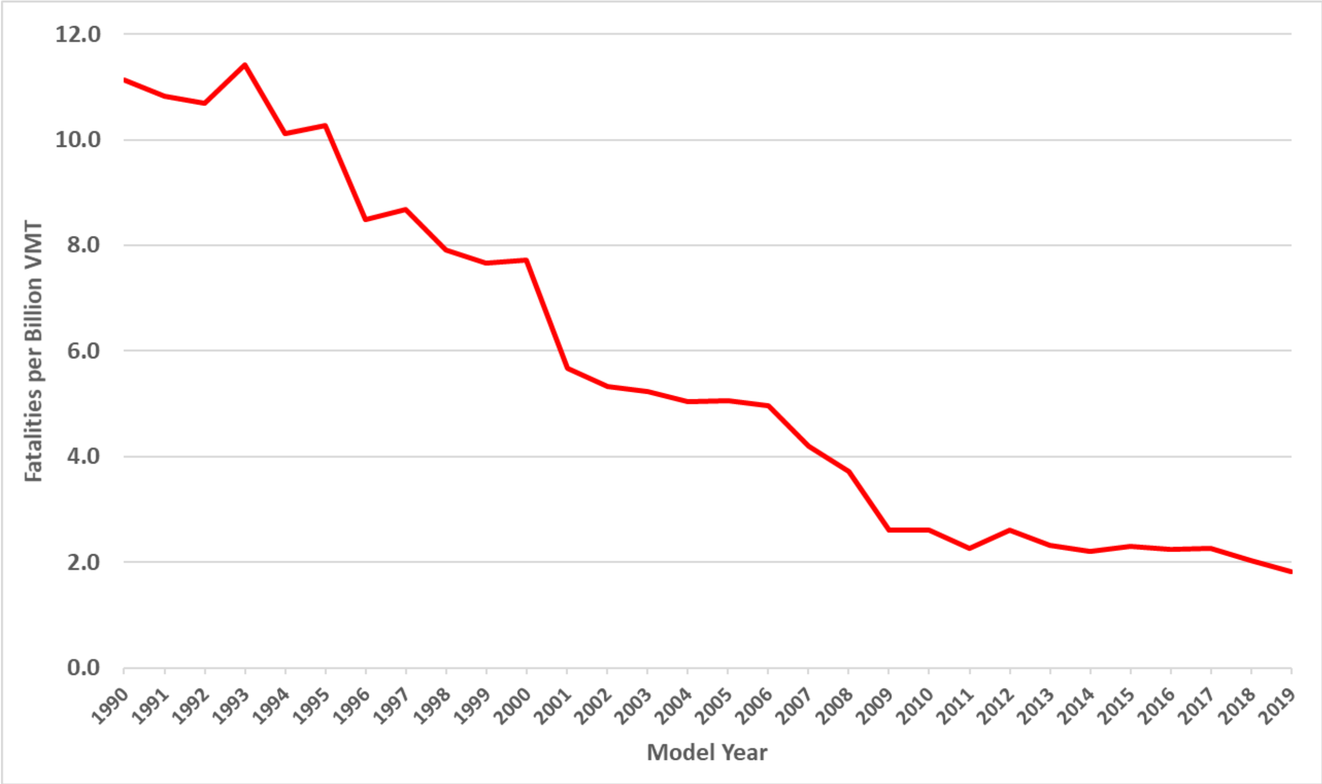
Figure 7-3 isolates the fatality rates for recent model years during the first years after each one is initially produced, sold, and initially registered for use.[1053] It clearly illustrates the gradual decline in new vehicles' fatality rates over successive model years, but it also shows that this decline has proceeded in fairly distinct steps rather than continuously. As the figure suggests, some of the largest improvements in new cars and light truck safety have coincided with the implementation of NHTSA safety regulations, including those requiring front-seat air bags (2000), side air bags (2006-08), and TPMS (2008).

To reflect the historical pattern of safety improvements shown in Figure 7-3, we group successive model years that had similar fatality rates when new into a smaller number of cohorts, based on visual examination of the figure and the effective dates of NHTSA safety regulations. Grouping model years in this way also enables more reliable identification of the effect of vehicle age, since it allows some independent variation in vehicles' ages within individual model year cohorts during any calendar year, rather than allowing age to be uniquely determined by the combination of calendar year and model year.

[1052] NHTSA. 2013. How Vehicle Age and Model Year Relate to Driver Injury Severity in Fatal Crashes. Report No. DOT HS 811 825). National Highway Traffic Safety Administration. Washington, D.C. Available at: https://crashstats.nhtsa.gov/Api/Public/ViewPublication/811825. (Accessed: Feb, 16, 2024).

[1053] Vehicles from each successive new model year are produced and sold over a period spanning well over a single calendar year, so we use their average fatality rate for the first two years they are represented in the fleet to be sure of including most or all vehicles from each model year.

Figure 7-3: Fatality Rates for New Light-Duty Vehicles



7.1.5. Factors that Affect Safety Over Time: Period Effects

As indicated previously, period effects are factors that vary over time and modify the gradual evolution in safety that results from the combination of introducing new, safer model year cohorts into the fleet and the effect of increasing age on safety. Period effects can influence the safety of all model years making up the fleet during the years when they occur, although they do not necessarily have the same effect on each model year's safety. One important example is the changing demographic composition of the driver population to include more older drivers and women; this trend improves overall safety because younger male drivers have historically been involved in more frequent crashes, but the resulting improvement differs by vehicle age. Another period effect on safety is the gradual shift of driving from rural to urban and suburban areas over time, since road conditions in the latter tend to be safer and travel speeds lower, thus reducing the frequency and severity of crashes.

Other important period influences on safety include driver behavior, since factors like the use of lap and shoulder belts – which has increased steadily since they were introduced but appears to be reaching a plateau – significantly reduce the severity of injuries vehicle occupants suffer in crashes. Other aspects of driving behavior such as driving under the influence of alcohol or electronic devices distracting drivers are linked to more frequent crashes. While driving under the influence has trended downward over the years and reduced crash incidence, distracted driving has become an increasingly common factor contributing to motor vehicle crashes. Still other period effects include gradual improvements in road design that reduce crash rates, such as wider travel lanes, more gradual curves, and removal of roadside obstructions. Faster response to crash situations by emergency vehicles and personnel, together with improved effectiveness of emergency medical treatment, also appear to have reduced the consequences of injuries to occupants of vehicles involved in crashes.

7.1.6. Measuring Safety

The agency developed separate statistical models to project future rates of fatalities, non-fatal injuries, and property damage-only crashes per billion vehicle miles of travel. Fatality rates were calculated by dividing fatalities to occupants of vehicles from each model year during a calendar year, as well as to non-occupants such as pedestrians and cyclists involved in crashes with them, by the total number of miles those vehicles were estimated to be driven (expressed in billion vehicle miles). The same procedure was used to calculate rates of non-fatal injuries and vehicles sustaining property damage per involved per billion vehicle miles. As indicated previously, fatalities were tabulated using NHTSA's FARS reporting system, while non-fatal injuries and vehicles sustaining property damage were estimated from NHTSA's GES and CRSS crash sampling systems using appropriate expansion weights for each crash type. The specific vehicle classes included in the agency's tabulation of fatalities, non-fatal injuries, and damaged vehicles include those that can clearly be identified as HDPUVs, but some vehicle classes used by NHTSA's reporting systems combine HDPUVs with larger trucks, and those were excluded. Thus, our tabulations of fatalities, non-fatal injuries, and vehicles sustaining property damage include those occurring in crashes involving some, but not all, HDPUVs, and the models we develop are used project their future values for both the light-duty and HDPUV fleets.

As discussed in detail in Chapter 4.3, the number of vehicle miles driven was estimated by multiplying the number of vehicles originally produced during each model year that are projected to remain use in a subsequent calendar year by the average number of miles that vehicles of their age are driven annually.[1054] This produces fatality rates by calendar year and model year for each calendar year from 1990-2019; the model years included range from 1975 (the earliest for which reliable registration data were available) to 2020 (the newest model year in the fleet during calendar year 2019). A similar process was used to calculate non-fatal injuries to light-duty vehicle occupants as well as non-occupants involved in crashes per billion miles driven, and the number of cars and light trucks involved in property damage-only crashes per billion miles driven.

Defining a model year's age as the number of calendar years since its introduction (age = calendar year – model year) transforms the fatality, non-fatal injury, and property damage rates from unique combinations of calendar year and model year to a smaller number of combinations of calendar year and age. Viewed from this perspective, each model year's safety is measured at different ages throughout its lifetime and combining these data for a succession of model years makes it possible to isolate model year and age-specific effects on overall safety. However, a model year's fatality rate during any subsequent calendar year will also reflect period-specific influences that are unique to that calendar year. Because each model year has a unique age during the calendar year when that specific combination of period effects prevailed, it is conceptually impossible to fully disentangle aging and period effects on any single model year's safety.[1055] We employ groups of model years with similar safety records during their initial year of use to address this problem, although this does not overcome it fully.

We use model years from 1975 through 2019 as a panel whose members are observed at different ages ranging from their first year in use (age=1) to an upper limit of 40, and employ fixed effects to represent model years.[1056] Because the data used to develop the model is shorter than 40 years, no single model year can be observed throughout its entire lifetime, but multiple model years are observed at every age over the entire range, so the effect of age should be measured reliably. Model years are typically observed for 13-14 years, with older model years observed only during the later years of their service lives, while the most recent model years are observed only at the very early ages of their expected lifetimes.[1057]

For example, the earliest model year included in calendar year 1990, the first year of the estimation period, is model year 1977, which by then had already reached age 14, while the newest model year observed in calendar year 2019 is model year 2019, defined to be of age = 1.[1058] The data used to derive these models

[1054] A model year's age during a past calendar year is equal to the difference between that calendar year and that model year. For example, vehicles produced during model year 2000 were age 10 during calendar year 2010, since 2010-2000 = 10.
[1055] Viewed another way, defining age = calendar year – model year means that there can be independent variation in only two of the three variables (since they uniquely determine the third), so it is impossible to identify their three separate effects on safety.
[1056] For an introduction to this method, see Wooldridge, Jeffrey M. 2009. Introductory Econometrics: A Modern Approach, 4th ed. South-Western Cengage Learning. Chapters 13 and 14.
[1057] Although the observation period is considerably shorter than the maximum number of years that a model year remains in the vehicle fleet, it is nevertheless longer than the 14-15 year "expected" lifetimes of light-duty vehicles, or the length of time that a typical car or LT remains in use after it is produced and initially sold.
[1058] Some vehicles of the next model year are sold and registered for use in each calendar year, and fatalities and injuries to their occupants (as well as any nonoccupants killed or injured in crashes involving them) and property damage they sustain are included with those of the current model year. For example, some model year 2020 cars and LTs were in use during calendar year 2019, and consequences of crashes they were involved during that year were included with those for model year 2019.

end in 2019 due to the time lag in reporting the crash and injury records included in NHTSA's FARS and CRSS, so the any impact of COVID-19 on long-term trends is incidentally excluded from this analysis. However, the agency feels that many of the changes to driving patterns during the pandemic represent an aberration to, and hence their exclusion likely enhances the precision of capturing long-term terms that will prevail over the coming decades.

As indicated above, the data used to construct the fatality model—and the injury and PDO models—appears to include some HDPUVs. NHTSA's body type codes for FARS generally combine vehicles under 10,000 lbs. GVWR, while some FARS classes combine vehicles over that weight threshold but still qualifying as HDPUVs with larger trucks, so constructing separate measures and models of safety for light-duty vehicles and HDPUVs was impracticable.[1059] The agency believes including these vehicles together in the analysis does not compromise the accuracy of the models, as HDPUVs and light-duty vehicles share many similar characteristics such as safety technologies, mass, and body-styles. For the same reasons, we calculate the safety effects of the final fuel efficiency standards for HDPUVs using the same fatality, non-fatal, and PDO models used to do so for light-duty vehicles.

7.1.7. Model Specification and Estimation

As discussed previously, we group successive model years with similar fatality or injury rates during their first year in use into "safety cohorts," and constrain the fixed effects for the model years making up each cohort to be identical. This provides some variation in the age of vehicles making up each cohort during any calendar year, which improves the models' ability to measure the independent effects of age and period variables. We group the 30 model years used in the fatality rate models that are observed when new into 10 safety cohorts, with some cohorts corresponding to only a single model year and others including as many as 8 consecutive model years. We use the same grouping of model years into cohorts for the non-fatal injury and property damage crash models.

As Figure 7-2 suggested, age also plays an important role in explaining the safety performance of model year cohorts over their lifetimes, although its effect appears complex – each cohort's fatality rate increases approximately linearly up to approximately age 15, but then levels off for some period and ultimately appears to decline, at least for those model years in our sample that reached ages above about 20 during the period we analyzed. To capture this pattern, all the model specifications we tested use both age and its squared value as explanatory variables, and some also include the cubed value of age in an effort to reproduce the pattern shown in Figure 7-2.

Table 7-1: Correlations Between Time-Varying Measures Affecting Safety

Variable	% of Licensed Drivers Male 16-24	% of VMT in Rural Areas	% of Occupants Wearing Lap and Shoulder Belts	% of Fatal Crashes Involving Drunk Driver	% of Drivers Using Hand-Held Devices
% of Licensed Drivers Male 16-24	1.00				
% of VMT in Rural Areas	0.89	1.00			

[1059] The agency's tabulations of fatalitites, non-fatal injureis, and vehicles sustaining property damage include those occurring in crashes involving the following FARS/CRSS body type codes: automobiles (codes 01-09), automobile derivatives (10-13), utility vehicles (14-16, 19, van-based LTs with GVWR less than 10,000 lbs. (20-22, 28-29), light conventional trucks with pickup style cabs and GVWR less than 10,000 lbs. (33-34, 39), other LTs with GVWR less than 10,000 lbs. (40-41, 45, 48-49), and medium/heavy pickup with GVWR less than 10,000 lbs. (67). See NHTSA, 2020 FARS/CRSS Coding and Validation Manual. DOT HS 813 251, March 2022, pp. 287-298. HDPUVs include all class 2b (8,501-10,000 lbs. GVWR) and some class 3 (10,001-14,000 GVWR) vehicles, so these tabulations appear to include many, but probably not all, HDPUVs.

% of Occupants Wearing Lap and Shoulder Belts	-0.94	-0.91	1.00		
% of Fatal Crashes Involving Drunk Driver	0.88	0.65	-0.75	1.00	
% of Drivers Using Hand- Held Devices	0.44	0.59	-0.66	0.32	1.00

As Table 7-1 shows, many of the period effect measures that would be obvious candidates for explanatory variables are closely correlated over the historical period (1990-2019) we analyze, making it nearly impossible to identify their independent effects. To address this difficulty, we substitute a linear time trend – a variable that takes the value of one in the first calendar year and increases by one in each successive year – to capture the effect of their joint movement over time on safety. We also experimented with more complex specifications to test whether the rate of improvement in fleet-wide safety has been constant over time, including using a non-linear time trend and testing for more abrupt changes in the rate of improvement in safety during the analysis period.[1060] As described in more detail below, we found that both of these variations improved the models' fit to the data, with both indicating that the rate of improvement in safety has slowed significantly over the period we analyzed. However, neither the simple linear nor the more complex time trends fully captured the effects on safety associated with the economic recessions in 1991, 2001-2, and 2008-11, so we supplemented the time trend with indicator (or "dummy") variables to capture temporary departures from the longer-term trend during those years. As described in more detail below, safety appears to improve consistently during these recession periods compared to the levels predicted using the time trend alone.

With minor variations, we used this same model specification to analyze trends in non-fatal injuries per billion miles driven by cars and light trucks, and in the number of those vehicles involved in crashes that resulted only in property damage per billion miles. The data used to estimate these models also spanned the shorter period from 1990 through 2019, during which NHTSA implemented a new crash sampling system, but we were able to overcome the difficulties in using the two systems to generate continuous and consistent data series for non-fatal injuries and property damage crashes spanning this period. As indicated previously, the groupings of model years into safety cohorts used in these models also differed slightly from that used in the fatality rate model.

7.1.8. Fatality Rate Model

Table 7-2 summarizes estimation results for alternative specifications of the fatality rate models, using the natural logarithm of fatalities per billion miles driven as their dependent variable. All of the model specifications include fixed effects for model year groups, which can be interpreted as those model years' estimated average fatality rate during their first year in use, individual model years' ages during each year of the estimation period, some form of time trend to capture the joint effects of time-varying or "period" variables (see below), and indicator variables to reflect transient declines in all model years' fatality rates during the recession years of 1991, 2009, and 2010. Continuous variables such as vehicle age and time appear in logarithmic form, while other variables are used in categorical form. More complex versions of the model also include interactions between model year groups and age as a test of whether the effect of age on fatality rates has changed for more recent model years. Overall, the alternative specifications reported in Table 7-2

[1060] Because the model's dependent variable is the natural logarithm of model year and age-specific fatality rates, using a linear time trend corresponds to assuming a constant percentage decline in fatality rates each year (rather than a constant absolute decline each year), and this pattern appeared to provide the best fit to the observed historical pattern of safety improvements.

replicate historical variation in fatality rates both among model years (as measured by the values of "Within R-squared") and over time ("Between R-squared") reasonably well.

As the table shows, after model years 1996-97 the estimated fixed effects for model year groups decline consistently over more recent model years in every specification, reflecting consistent reductions in new vehicles' fatality rates with successive transitions from one model year "cohort" to the next.[1061] The consistently positive value of the fixed effect for model years 1996-97 indicates that fatality rates for new vehicles produced during those model years *increased* compared to model years 1990-95 (whose fatality rates when new are reflected in the model's constant term), which may reflect the rapid shift in sales of new vehicles from automobiles toward light-duty trucks – which generally exhibited higher fatality rates than autos – during the mid-1990s. In nearly all specifications, the largest declines in new vehicles' fatality rates appear to have occurred with the introduction of model years 1998 and 2010, with consistent but more modest reductions beginning with model years 2003, 2006, 2007, and 2008, and much smaller reductions when more recent model years were introduced. The values of the diagnostic statistic rho reported in the last line of the table, which measures the proportion of the variation in fatality rates explained by each model that is accounted for by its fixed effects, indicate that improvements in the safety of new cars and light trucks explain much of the overall improvement in fleet-wide safety.

Extensive testing previously confirmed the difficulty of identifying the separate effects of individual period effect variables on fatality rates.[1062] To summarize those results briefly, the unemployment rate and use of lap and shoulder belts each appear to reduce fatality rates significantly when used alone in the model, but in combination their effects are muted. Driving under the influence of alcohol is also by itself strongly associated with higher fatality rates but including any combination of those three variables in the model vastly reduces the precision of their estimated effects and can sometimes even change their apparent direction. Increased drivers' use of hand-held electronic devices appears to *reduce* fatality rates when it is added to the model, but this result so strongly contradicts expectations that it must be regarded skeptically and interpreted as a possible artifact of the difficulty of measuring its growth accurately or its close correlation with both unemployment and alcohol use. Positive coefficient estimates for the fraction of licensed drivers who are young males and the fraction of travel in rural areas suggest that declines over time in both of these measures have contributed significantly to the decline in fatality rates, but again, using either one in conjunction with other time-varying measures causes pronounced changes in their estimated coefficients (sometimes including changes in their arithmetic signs) and makes all of their apparent effects suspect.

The difficulty of obtaining plausible estimates of the independent contributions of more than one period variable suggests that substituting a time trend may be a sensible alternative. Another advantage of doing so is that it avoids the need to obtain reliable forecasts of factors measured by the period variables such as unemployment, use of seat belts and smartphones, and driving under the influence of alcohol, all of which have complex underlying causes that make their future patterns difficult to project. (Of course, extrapolating a time trend into the future implicitly assumes that the factors it represents will continue to change and affect safety in the same ways they have in the recent past.) Thus, all the specifications for which Table 7-2 reports estimation results employ some form of time trend. As the results for Models 1-4 indicate, the combination of fixed effects for model year groups, vehicle age, and a time trend explains much of the variation in fatality rates, both among model years at identical ages and for individual model years as their ages increase. Linear, squared, and cubed values of age all show statistically significant effects on fatality rates, and in combination generally reproduce the pattern shown previously in Figure 7-2 well. Estimated coefficients for the variables indicating recessions in 1991, 2009, and 2010 show that fatality rates temporarily declined to levels well below those predicted by either form of the downward trend during some recession years.

With one exception (Model 3), coefficient estimates for the time trend variable and its square consistently indicate that some combination of the period effects it is intended to capture reduced fatality rates, typically by 1-3 percent annually, early in the estimation period. However, the sign and magnitude of the estimated coefficient for the square of the trend variable in Models 2, 4-6, and 10-11 suggests that the initial decline in

[1061] In some cases the decline in the estimated values of the fixed effect from one model year cohort to the next newer one is not statistically significant, but we elected to retain the groupings since they were determined partly by a priori expectations based on the introduction of NHTSA safety standards, which are typically required or phased in beginning with a specific model year.
[1062] These specification tests were described in detail and their econometric results were reported in the TSD accompanying the 2022 final rule, so they are summarized here.

fatality rates has slowed substantially throughout the estimation period. As an illustration, Model 2 suggests that after controlling for the changing model year composition and age distribution of the car and light truck fleet, the overall fatality rate declined by about 3% annually at the outset of the estimation period (1990), but that this decline slowed to well under 1% annually within several years and to only about 0.1% by its end in 2019. Alternative specifications allowing for a one-time "flattening" of the downward historical trend in the fatality rate in calendar year 2007 (Models 7-9 and 12-14) fit the data nearly as well but consistently suggest much slower initial declines in the overall fatality rate (slightly less than 1% annually), accompanied by a sharp "flattening" (and in some cases even a reversal) of its downward trend beginning in 2007.

Models 5-6, 8-11, and 13-14 allow interactions between model year cohorts and age to test whether the form of the effect of aging on fatality rates has changed for more recent model years, although Figure 7-1 above suggested that any such change does not appear to be pronounced. The form of this interaction is quite restrictive, as it implies that the effects of age (and its squared value, where included) change by equal *increments* with each successive model year cohort, but the coefficient estimates for those models do suggest that the increase in fatality rates through vehicles' early ages has become slightly less steep for more recent model years. This result is so consistent that although we have only observed fatality rates for the most recent model year groups (which include cars and light trucks beginning with model year 2010) through a maximum age of ten years, we rely on the estimated aging effect for these cohorts to develop projections of recent and future model years' fatality rates throughout their lifetimes under the reference baseline alternative.

Specifically, we employ the coefficient estimates for Model 11 reported in Table 7-2 to forecast reference baseline fatality rates for model years making up the future fleet. We elected to use this particular specification because it includes all variables that appear to contribute significantly to explaining historical variation in fatality rates (including a time trend whose "steepness" declines throughout the estimation period and age effects that are less pronounced for more recent model years), their estimated effects have the anticipated directions and plausible magnitudes, its fixed effects for model year groups have the anticipated declining pattern moving toward more recent model years, and it fits the data as well or better than any of the alternative specifications we tested. An alternative would have been to use a specification whose estimated aging effect also reflected the experience with older model years rather than just the most recent ones, but this seemed likely to overstate the influence of aging on fatality rates for the model years that will comprise the future fleets. Because as discussed previously the counts of fatalities, injuries, and vehicles sustaining property damage in crashes included some (but not all) HDPUV models, we also use these same estimation results to project future fatality rates for HDPUVs under the reference baseline alternative.

Table 7-2: Estimation Results for Fatality Rate Models

Explanatory Variables	Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)						
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Constant (Model Years 1990-95)	2.007***	2.196***	1.916***	2.117***	2.180***	2.256***	2.108***
	(0.028)	(0.033)	(0.032)	(0.038)	(0.037)	(0.038)	(0.030)
MY 1996-97	0.0902***	0.110***	0.0866***	0.106***	0.133***	0.0201	0.105***
	(0.026)	(0.025)	(0.025)	(0.024)	(0.034)	(0.037)	(0.025)
MY 1998-2002	-0.167***	-0.128***	-0.182***	-0.142***	-0.0914*	-0.202***	-0.132***
	(0.039)	(0.038)	(0.039)	(0.037)	(0.053)	(0.054)	(0.038)
MY 2003-05	-0.352***	-0.314***	-0.370***	-0.330***	-0.269***	-0.355***	-0.314***
	(0.050)	(0.048)	(0.049)	(0.047)	(0.066)	(0.065)	(0.048)
MY 2006	-0.490***	-0.457***	-0.508***	-0.472***	-0.406***	-0.471***	-0.456***
	(0.067)	(0.064)	(0.066)	(0.063)	(0.083)	(0.081)	(0.064)
MY 2007	-0.614***	-0.584***	-0.631***	-0.599***	-0.526***	-0.577***	-0.584***
	(0.070)	(0.066)	(0.069)	(0.066)	(0.089)	(0.087)	(0.067)

MY 2008-09	-0.744***	-0.721***	-0.758***	-0.733***	-0.659***	-0.686***	-0.724***
	(0.064)	(0.061)	(0.063)	(0.060)	(0.088)	(0.086)	(0.061)
MY 2010	-0.926***	-0.906***	-0.935***	-0.914***	-0.842***	-0.843***	-0.910***
	(0.079)	(0.075)	(0.078)	(0.075)	(0.100)	(0.097)	(0.076)
MY 2011-17	-1.069***	-1.066***	-1.060***	-1.060***	-1.010***	-0.989***	-1.074***
	(0.068)	(0.065)	(0.067)	(0.064)	(0.086)	(0.084)	(0.065)
MY 2018-19	-1.069***	-1.110***	-1.022***	-1.072***	-1.075***	-1.086***	-1.117***
	(0.127)	(0.121)	(0.125)	(0.120)	(0.126)	(0.122)	(0.121)
ln Age	0.0887***	0.0918***	0.116***	0.111***	0.0962***	0.0883***	0.0912***
	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)	(0.005)	(0.003)
ln Age^2	-0.00238***	-0.00243***	-0.00415***	-0.00371***	-0.00250***	-0.00289***	-0.00242***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln Age^3			3.06e-05***	2.21e-05***			
			(0.000)	(0.000)			
ln Time	-0.00376*	-0.0310***	0.00410**	-0.0282***	-0.0337***	-0.0184***	-0.00895***
	(0.002)	(0.004)	(0.002)	(0.004)	(0.005)	(0.005)	(0.002)
ln Time^2		0.000997***		0.000924***	0.00108***	0.000589***	
		(0.000)		(0.000)	(0.000)	(0.000)	
1991	-0.0959*	-0.242***	-0.105**	-0.238***	-0.243***	-0.242***	-0.190***
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.049)	(0.049)
2009	-0.253***	-0.197***	-0.243***	-0.194***	-0.198***	-0.196***	-0.143***
	(0.031)	(0.030)	(0.031)	(0.030)	(0.030)	(0.029)	(0.033)
2010	-0.173***	-0.123***	-0.164***	-0.121***	-0.125***	-0.122***	-0.0939***
	(0.031)	(0.030)	(0.030)	(0.030)	(0.030)	(0.029)	(0.035)
Trend Shift							-0.627***
							(0.097)
Trend Shift x ln Time							0.0319***
							(0.004)
MY Group x ln Age					-0.00125	-0.00786***	
					(0.001)	(0.002)	
MY Group x ln Age^2						0.000675***	
						(0.000)	
Observations	891	891	891	891	891	891	891
R2	0.859	0.873	0.863	0.875	0.873	0.880	0.872
R2 within	0.663	0.697	0.675	0.702	0.697	0.714	0.694
R2 between	0.879	0.938	0.824	0.897	0.974	0.969	0.937
sigma_u	0.424	0.435	0.416	0.428	0.423	0.390	0.437
sigma_e	0.180	0.171	0.177	0.169	0.171	0.166	0.172
rho	0.848	0.866	0.847	0.864	0.859	0.846	0.866

Corr(ui,xb)	0.240	0.245	0.232	0.242	0.294	0.311	0.242

Table 7-2 (continued): Estimation Results for Fatality Rate Models

Explanatory Variables	**Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)**						
	Model 8	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**
Constant (Model Years 1990-95)	2.094***	2.213***	2.030***	2.017***	2.035***	1.943***	1.979***
	(0.039)	(0.041)	(0.047)	(0.045)	(0.035)	(0.049)	(0.047)
MY 1996-97	0.119***	0.00918	0.185***	0.0569	0.101***	0.166***	0.0449
	(0.034)	(0.036)	(0.035)	(0.035)	(0.025)	(0.035)	(0.035)
MY 1998-2002	-0.111**	-0.216***	-0.0197	-0.128**	-0.146***	-0.0465	-0.143***
	(0.053)	(0.053)	(0.054)	(0.052)	(0.038)	(0.054)	(0.051)
MY 2003-05	-0.287***	-0.366***	-0.181***	-0.235***	-0.330***	-0.207***	-0.249***
	(0.066)	(0.065)	(0.067)	(0.064)	(0.048)	(0.067)	(0.063)
MY 2006	-0.425***	-0.482***	-0.300***	-0.307***	-0.471***	-0.328***	-0.321***
	(0.083)	(0.081)	(0.084)	(0.079)	(0.064)	(0.084)	(0.079)
MY 2007	-0.549***	-0.590***	-0.402***	-0.372***	-0.598***	-0.436***	-0.387***
	(0.089)	(0.087)	(0.091)	(0.086)	(0.066)	(0.091)	(0.086)
MY 2008-09	-0.687***	-0.701***	-0.522***	-0.444***	-0.735***	-0.561***	-0.460***
	(0.088)	(0.085)	(0.091)	(0.086)	(0.061)	(0.091)	(0.086)
MY 2010	-0.872***	-0.858***	-0.695***	-0.568***	-0.918***	-0.737***	-0.584***
	(0.100)	(0.097)	(0.102)	(0.097)	(0.075)	(0.102)	(0.097)
MY 2011-17	-1.041***	-1.004***	-0.864***	-0.705***	-1.067***	-0.908***	-0.721***
	(0.086)	(0.083)	(0.090)	(0.086)	(0.064)	(0.089)	(0.085)
MY 2018-19	-1.097***	-1.097***	-0.938***	-0.837***	-1.079***	-0.972***	-0.851***
	(0.126)	(0.122)	(0.127)	(0.120)	(0.121)	(0.127)	(0.120)
ln Age	0.0938***	0.0868***	0.134***	0.154***	0.110***	0.129***	0.152***
	(0.005)	(0.005)	(0.009)	(0.009)	(0.006)	(0.009)	(0.009)
ln Age^2	-0.00246***	-0.00288***	-0.00441***	-0.00666***	-0.00369***	-0.00426***	-0.00665***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln Age^3			3.02e-05***	5.63e-05***	2.19e-05***	2.85e-05***	5.63e-05***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln Time	-0.00944***	-0.00515**	-0.0364***	-0.0154***	-0.00763***	-0.00961***	-0.00324
	(0.003)	(0.003)	(0.005)	(0.005)	(0.002)	(0.003)	(0.002)
ln Time^2			0.00118***	0.000518***			
			(0.000)	(0.000)			
1991	-0.188***	-0.213***	-0.238***	-0.232***	-0.188***	-0.177***	-0.204***
	(0.049)	(0.048)	(0.049)	(0.047)	(0.049)	(0.049)	(0.046)
2009	-0.141***	-0.165***	-0.197***	-0.193***	-0.146***	-0.138***	-0.171***
	(0.033)	(0.032)	(0.030)	(0.028)	(0.033)	(0.033)	(0.031)

2010	-0.0926***	-0.106***	-0.125***	-0.121***	-0.0927***	-0.0861**	-0.100***
	(0.035)	(0.034)	(0.029)	(0.028)	(0.035)	(0.035)	(0.033)
Trend Shift	-0.660***	-0.348***			-0.583***	-0.731***	-0.324***
	(0.113)	(0.117)			(0.097)	(0.112)	(0.112)
Trend Shift x In Time	0.0336***	0.0178***			0.0295***	0.0368***	0.0159***
	(0.005)	(0.005)			(0.004)	(0.005)	(0.005)
MY Group x In Age	-0.000736	-0.00783***	-0.00434***	-0.0172***		-0.00357**	-0.0171***
	(0.001)	(0.002)	(0.001)	(0.002)		(0.001)	(0.002)
MY Group x In Age^2		0.000697***		0.00103***			0.00106***
		(0.000)		(0.000)			(0.000)
Observations	891	891	891	891	891	891	891
R2	0.872	0.880	0.876	0.891	0.874	0.875	0.890
R2 within	0.695	0.713	0.706	0.739	0.700	0.702	0.738
R2 between	0.963	0.960	0.970	0.990	0.898	0.974	0.989
sigma_u	0.429	0.392	0.381	0.293	0.429	0.391	0.296
sigma_e	0.172	0.166	0.169	0.159	0.170	0.170	0.159
rho	0.862	0.848	0.836	0.773	0.864	0.841	0.775
Corr(ui,xb)	0.273	0.293	0.375	0.529	0.240	0.361	0.516

7.1.9. Non-Fatal Injury Rates

Table 7-3 reports estimation results for a similar set of models that explain historical variation in non-fatal injuries to occupants of light-duty vehicles and HDPUVs, and non-occupants (again, primarily pedestrians and cyclists) involved in crashes with them. As with the fatality rate model, the dependent variable in all model specifications summarized in the table is the natural logarithm of the number of non-fatal injuries to occupants and non-occupants per billion miles traveled by cars and light trucks. This rate again varies both among model years of different ages during any calendar year, as well as for each model year over the span of calendar years when it is represented in the data sample.

The alternative specifications reported in Table 7-3 group model years from 1990 through 2019, those observed during their respective first years of use, into the same 10 cohorts as the fatality rate model described in Chapter 7.1.8 above. The models for non-fatal injury rates also employ the time trend variables discussed previously to help capture the combined effects of a number of time-varying or period influences on safety, which are too closely correlated with one another to enable their separate effects to be identified reliably. Some specifications also test whether the effect of aging on injury rates has changed during more recently introduced model years.

The coefficient estimates for model year groups reported in Table 7-3 (again, the constant term represents the fatality rate for the earliest model years to appear as new vehicles in the estimating sample, 1990-1995) reveal the same initial increase in injury rates for model years 1996-97 as was evident for fatality rates, but do not show the same systematic decline for more recent model years as was evident with fatality rates. It is possible that this masks an improvement in the safety of new models over time, with declines over time in more severe injuries offset by increases in minor injuries, and examining injury trends for individual severity categories suggests that this may be the case. Partly as a consequence of the limited explanatory power of fixed effects for the model year cohorts, the models for injury rates do not explain observed variation as well as did those for fatality rates, as shown by the various R-squared measures reported in Table 7-3.

Results for Models 1-4 shows that the combination of age, a time trend – which is again included to represent the joint effects of several time-varying period influences that are too closely correlated to disentangle – and indication variables for selected recession years explains the variation in injury rates over time and among model years nearly as well as more complex specifications. Including both squared and cubed values of vehicle age (Models 3 and 4) improves the models' ability to replicate the observed pattern of injury rates across ages, which closely resembles that shown for fatalities in Figure 7-2 above, although without the consistent downward shift in the entire curve.

The time trend variables again suggest very rapid declines in injury rates across all model years in use at the beginning of the estimation period in 1990, in a few cases exceeding 10% annually (Models 2-5). However, allowing the trend to "flatten" over time by including its squared value (Models 2 and 4-6) again suggests rapid slowing of that initial decline, to 1-2% annually within a decade and well under 1% by the end of the estimation period. Similarly, specifying a one-time change in the strength of the initial downward trend in injury rates starting with calendar year 2007 (Models 7-9 and 12-14) suggests that injury rates declined approximately 5% annually until then but may have increased very slowly since. In contrast to the fatality rate models, indicator variables for recession years show only weak and rarely significant effects beyond those captured by time trends alone.

Coefficient estimates for the variables capturing interactions between age and model year groupings, which appear in Models 5-6, 8-11, and 13-14, reveal a weaker effect of age on injury rates for more recent model years. Thus, while more recent model years do not have significantly reduced injury rates when new compared to their predecessors, neither do their injury rates appear to increase as rapidly with age as did their predecessors'.

On balance, none of the models explains variation in injury rates particularly well, either among model year cohorts observed at the same age or as individual cohorts age and accumulate use. Thus, it is difficult to choose a single "best performing" model to use for projecting future evolution of injury rates under the reference baseline alternative. Mainly for consistency with its forecasts of fatality rates, the agency has developed the forecasts of baseline injury rates it uses to analyze the safety consequences of slowing sales of new cars and trucks and increasing retention of older model years using the coefficient estimates for Model 11 shown in Table 7-3. As with fatality rates, this specification has the advantages of including all variables that contribute significantly to explaining historical variation in fatality rates, their estimated effects have the "correct" directions and reasonable magnitudes, and it fits the data as well as any alternative specification we tested.

Table 7-3: Estimation Results for Non-Fatal Injury Rate Models

Explanatory Variables	Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant (Model Years 1990-95)	6.781***	7.329***	6.549***	7.136***	7.344***	7.405***	7.110***
	(0.075)	(0.087)	(0.086)	(0.100)	(0.098)	(0.102)	(0.076)
MY 1996-97	0.239***	0.296***	0.230***	0.286***	0.275***	0.186*	0.289***
	(0.068)	(0.065)	(0.067)	(0.064)	(0.090)	(0.099)	(0.064)
MY 1998-2002	0.0403	0.155	0.00182	0.121	0.122	0.0339	0.156
	(0.104)	(0.098)	(0.103)	(0.098)	(0.139)	(0.145)	(0.097)
MY 2003-05	-0.0588	0.0518	-0.106	0.0127	0.0122	-0.0556	0.0678
	(0.132)	(0.125)	(0.131)	(0.124)	(0.173)	(0.175)	(0.123)
MY 2006	-0.013	0.0836	-0.059	0.0462	0.0381	-0.0136	0.102
	(0.178)	(0.167)	(0.175)	(0.166)	(0.217)	(0.217)	(0.165)
MY 2007	0.0813	0.168	0.038	0.133	0.116	0.076	0.184
	(0.185)	(0.174)	(0.182)	(0.173)	(0.233)	(0.234)	(0.172)
MY 2008-09	0.0124	0.0794	-0.0241	0.0503	0.0242	0.00307	0.0832

	(0.169)	(0.159)	(0.167)	(0.158)	(0.230)	(0.230)	(0.157)
MY 2010	-0.196	-0.137	-0.22	-1.57E-01	-0.194	-0.195	-0.14
	(0.209)	(0.197)	(0.206)	(0.195)	(0.261)	(0.261)	(0.194)
MY 2011-17	-0.113	-0.104	-0.0924	-0.0899	-0.153	-0.136	-0.128
	(0.180)	(0.169)	(0.177)	(0.168)	(0.225)	(0.225)	(0.167)
MY 2018-19	-0.107	-0.223	0.0147	-0.132	-0.253	-0.262	-0.266
	(0.336)	(0.316)	(0.331)	(0.314)	(0.329)	(0.329)	(0.312)
ln Age	0.0489***	0.0577***	0.119***	0.105***	0.0538***	0.0474***	0.0569***
	(0.008)	(0.008)	(0.016)	(0.015)	(0.014)	(0.015)	(0.008)
ln Age2	-0.00189***	-0.00203***	-0.00645***	-0.00515***	-0.00197***	-0.00229***	-0.00201***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
ln Age3			7.89e-05***	5.41e-05***			
			(0.000)	(0.000)			
ln Time	-0.0146***	-0.115***	-0.0138**	-0.108***	-0.113***	-0.100***	-0.0558***
	(0.005)	(0.011)	(0.005)	(0.011)	(0.013)	(0.014)	(0.006)
ln Time2		0.00288***		0.00270***	0.00280***	0.00241***	
		(0.000)		(0.000)	(0.000)	(0.000)	
1991	0.165	-0.257*	0.143	-0.247*	-0.257*	-0.256*	-0.139
	(0.133)	(0.131)	(0.131)	(0.130)	(0.131)	(0.131)	(0.127)
2009	-0.314***	-0.153*	-0.290***	-0.146*	-0.152*	-0.151*	0.0377
	(0.083)	(0.079)	(0.082)	(0.079)	(0.079)	(0.079)	(0.085)
2010	-0.171**	-0.0285	-0.149*	-0.0225	-0.0273	-0.0253	0.101
	(0.082)	(0.078)	(0.081)	(0.077)	(0.078)	(0.078)	(0.090)
Trend Shift							-2.112***
							(0.250)
Trend Shift x ln Time							0.106***
							(0.010)
MY Group x ln Age					0.00111	-0.00416	
					(0.003)	(0.004)	
MY Group x ln Age2						0.000537**	
						(0.000)	
Observations	891	891	891	891	891	891	891
R2	0.422	0.490	0.440	0.498	0.490	0.493	0.504
R2 within	0.362	0.437	0.382	0.446	0.437	0.440	0.453
R2 between	0.731	0.639	0.626	0.825	0.546	0.713	0.276
sigma_u	0.120	0.157	0.117	0.134	0.160	0.132	0.169
sigma_e	0.476	0.448	0.469	0.444	0.448	0.447	0.442
rho	0.060	0.109	0.058	0.084	0.114	0.080	0.128
Corr(ui,xb)	0.181	0.145	0.145	0.155	0.145	0.199	0.140

Table 7-3 (continued): Estimation Results for Non-Fatal Injury Rate Models

Explanatory Variables	Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)						
	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
Constant (Model Years 1990-95)	7.085***	7.156***	7.027***	7.012***	6.943***	6.748***	6.779***
	(0.099)	(0.108)	(0.125)	(0.124)	(0.089)	(0.128)	(0.127)
MY 1996-97	0.313***	0.247***	0.385***	0.246**	0.281***	0.418***	0.305***
	(0.087)	(0.095)	(0.093)	(0.098)	(0.063)	(0.090)	(0.095)
MY 1998-2002	0.193	0.13	0.274*	0.156	0.125	0.338**	0.247*
	(0.136)	(0.140)	(0.143)	(0.144)	(0.097)	(0.139)	(0.140)
MY 2003-05	0.113	0.0664	0.199	0.14	0.031	0.293*	0.255
	(0.170)	(0.172)	(0.177)	(0.176)	(0.123)	(0.174)	(0.173)
MY 2006	0.155	0.121	0.262	0.254	0.0671	0.372*	0.380*
	(0.213)	(0.214)	(0.222)	(0.220)	(0.164)	(0.218)	(0.216)
MY 2007	0.243	0.219	0.378	0.413*	0.151	0.498**	0.545**
	(0.230)	(0.230)	(0.240)	(0.238)	(0.171)	(0.236)	(0.234)
MY 2008-09	0.147	0.139	0.314	0.401*	0.057	0.429*	0.526**
	(0.226)	(0.226)	(0.239)	(0.238)	(0.157)	(0.235)	(0.234)
MY 2010	-0.0749	-0.0662	0.117	0.256	-0.157	0.228	0.374
	(0.257)	(0.256)	(0.270)	(0.270)	(0.193)	(0.265)	(0.265)
MY 2011-17	-0.0713	-0.049	0.155	0.33	-0.114	0.227	0.404*
	(0.220)	(0.221)	(0.236)	(0.238)	(0.166)	(0.230)	(0.233)
MY 2018-19	-0.232	-0.232	0.0359	0.148	-0.183	0.0474	0.162
	(0.324)	(0.324)	(0.334)	(0.332)	(0.311)	(0.329)	(0.328)
ln Age	0.0614***	0.0572***	0.133***	0.156***	0.101***	0.140***	0.162***
	(0.014)	(0.014)	(0.024)	(0.025)	(0.015)	(0.024)	(0.024)
ln Age2	-0.00208***	-0.00233***	-0.00603***	-0.00852***	-0.00489***	-0.00612***	-0.00840***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln Age3			6.43e-05***	9.34e-05***	5.00e-05***	6.43e-05***	9.09e-05***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln Time	-0.0566***	-0.0541***	-0.118***	-0.0955***	-0.0528***	-0.0570***	-0.0510***
	(0.007)	(0.007)	(0.013)	(0.014)	(0.006)	(0.007)	(0.007)
ln Time2			0.00302***	0.00230***			
			(0.000)	(0.000)			
1991	-0.135	-1.50E-01	-0.247*	-0.241*	-1.35E-01	-0.111	-0.137
	(0.127)	(0.127)	(0.130)	(0.129)	(0.126)	(0.126)	(0.125)
2009	0.0407	0.0266	-0.150*	-0.145*	0.0314	0.0478	0.0168
	(0.085)	(0.086)	(0.079)	(0.078)	(0.084)	(0.085)	(0.084)
2010	0.103	0.0953	-0.0273	-0.0232	0.105	0.119	0.106
	(0.090)	(0.090)	(0.077)	(0.077)	(0.090)	(0.090)	(0.089)

Trend Shift	-2.169***	-1.983***			-2.017***	-2.332***	-1.954***
	(0.290)	(0.309)			(0.250)	(0.290)	(0.305)
Trend Shift x In Time	0.109***	0.0997***			0.101***	0.117***	0.0970***
	(0.013)	(0.014)			(0.010)	(0.013)	(0.014)
MY Group x In Age	-0.00127	-0.0055	-0.00542	-0.0195***		-0.00762**	-0.0204***
	(0.003)	(0.004)	(0.004)	(0.005)		(0.004)	(0.005)
MY Group x In Age2		0.000415*		0.00113***			0.001000***
		(0.000)		(0.000)			(0.000)
Observations	891	891	891	891	891	891	891
R2	0.504	0.506	0.499	0.509	0.511	0.514	0.521
R2 within	0.453	0.455	0.448	0.459	0.461	0.463	0.472
R2 between	0.248	0.489	0.514	0.640	0.770	0.294	0.482
sigma_u	0.168	0.146	0.135	0.128	0.145	0.163	0.165
sigma_e	0.442	0.441	0.444	0.440	0.439	0.438	0.435
rho	0.127	0.099	0.084	0.078	0.099	0.121	0.125
Corr(ui,xb)	0.122	0.190	0.013	-0.038	0.154	-0.079	-0.134

7.1.10. Property Damage Rates

Table 7-4 reports the results of estimating identical model specifications for crashes that cause only damage to vehicles or immediately surrounding property. As indicated above, counts of vehicles sustaining property damage were obtained from NHTSA's GES and CRSS crash sampling systems, expanded to represent nationwide totals using appropriate weights for each crash type, and divided by estimated vehicle miles to develop property damage rates. In Table 7-4, the dependent variable of each model is the natural logarithm of the number of *vehicles* involved in property damage only crashes per billion vehicle miles driven by cars, light trucks, and HDPUVs, and this measure once again varies across model years (and thus vehicles of different ages) in use during each calendar year, as well as with each model year's increasing age. Summary statistics reported for each specification indicate that these models generally do a better job of explaining those two sources of variation than was the case for injury rates, although they still do not perform quite as well as those for fatality rates.

All specifications of the property damage equations group model years into the same 10 cohorts used to analyze fatality and non-fatal injury rates. As with those measures, the estimated fixed effects for model years 1996-97 consistently suggest significant increases in property damage rates for those vehicles when they were newly introduced, compared to the previous several model years. Estimated fixed effects for newer model year cohorts rarely indicate statistically reliable changes, but where they do (Models 10-11 and 13-14) they imply consistent *increases* in property damage rates for more recent model years when new, in contrast to the consistent decline in new vehicles' fatality rates over time. This may be a consequence of more frequent reporting of PDO crashes due to the escalating costs to repair damage to more recent models, which often employ designs, materials, or on-board technologies that are more vulnerable in crashes or costly to repair, so crash-inflicted damages more often exceed thresholds for official reporting or filing insurance claims.

As with fatality and injury rates, Table 7-4 shows that the combination of model-year fixed effects, increasing vehicle age, and changing period effects over time explains most of the variation in property damage rates, both among model years and over the range of ages they are observed in the estimating data. Coefficient estimates for the time variable reported in Table 7-4 indicate that after controlling for model years' initial differences and age, the same downward trend observed for fatality and non-fatal injury rates also applies in the case of property damage crashes, although the implied estimates of its strength at the outset of the estimation period vary from as low as a 2% annual decline (in Models 7-9 and 12-14) to more than double that rate in other specifications.

As previously discussed, coefficient estimates for specifications allowing a gradually weakening downward trend in the property damage rate (Models 2, 4-6, and 20-11) suggest that it eroded rapidly to less than 1% during the first decade after 1990, while estimates for specifications that allow a one-time flattening of the downward trend (Models 7-9 and 12-14) in approximately the middle of the estimation period suggest that it completely disappeared thereafter. Again, one possible explanation for this result is that crashes resulting in significant property damage but causing no injuries have become more common in recent years as vehicles have become better at protecting their occupants in crashes but increasingly complex in design and on-board technology, and thus morel likely to be damaged in crashes and more costly to repair. With occasional exceptions for 2009, indicator variables for recession years do not add significant explanatory power to specifications that allow for flattening of their downward time trends.

Choosing a best model to use for developing forecasts of property damage rates for the future vehicle fleet is once again challenging. Because it features statistically significant fixed effects for most model year cohorts, effects of vehicle age that diminish for more recent model years (an effect that appears consistent with the increased duration of typical vehicle ownership), and a plausibly behaved pattern of decline in property damage rates over time, the agency has again elected to use the estimated coefficients for Model 11 in Table 7-4 to develop forecasts of property damage rates for the future light-duty fleet. The following subchapter explains how NHTSA uses the models it selected to forecast the evolution of fatality, injury, and property damage rates under the reference baseline alternative, including accounting for the increasing adoption and effectiveness of technologies that assist buyers and drivers of new vehicles in avoiding crashes.

Table 7-4: Estimation Results for Property Damage Only Crashes

Explanatory Variables	Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant (Model Years 1990-95)	7.765***	8.061***	7.642***	7.960***	8.047***	8.083***	7.939***
	(0.034)	(0.038)	(0.039)	(0.044)	(0.043)	(0.045)	(0.034)
MY 1996-97	0.145***	0.176***	0.141***	0.171***	0.195***	0.143***	0.170***
	(0.031)	(0.028)	(0.030)	(0.028)	(0.040)	(0.044)	(0.028)
MY 1998-2002	0.0928**	0.155***	0.0723	0.137***	0.184***	0.133**	0.150***
	(0.047)	(0.043)	(0.046)	(0.043)	(0.061)	(0.064)	(0.043)
MY 2003-05	0.0493	0.109**	0.0242	0.0885	0.145*	0.106	0.111**
	(0.060)	(0.055)	(0.059)	(0.055)	(0.076)	(0.077)	(0.055)
MY 2006	0.0749	0.127*	0.0504	0.107	0.169*	0.139	0.129*
	(0.081)	(0.074)	(0.079)	(0.073)	(0.095)	(0.096)	(0.074)
MY 2007	0.0669	0.114	0.0438	0.0951	0.161	0.137	0.113
	(0.084)	(0.077)	(0.082)	(0.076)	(0.103)	(0.103)	(0.077)
MY 2008-09	0.0593	0.0955	0.0398	0.0801	0.146	0.134	0.0878
	(0.077)	(0.070)	(0.075)	(0.070)	(0.102)	(0.101)	(0.070)
MY 2010	-0.00404	0.0277	-0.0169	0.0171	0.0795	0.0792	0.0156
	(0.095)	(0.087)	(0.093)	(0.086)	(0.115)	(0.115)	(0.087)
MY 2011-17	-0.0332	-0.028	-0.0222	-0.0209	0.0171	0.0269	-0.0413
	(0.082)	(0.074)	(0.080)	(0.074)	(0.099)	(0.099)	(0.074)
MY 2018-19	-0.0827	-0.145	-0.0179	-0.0975	-0.117	-0.122	-0.146

	(0.152)	(0.139)	(0.149)	(0.138)	(0.145)	(0.144)	(0.139)
ln Age	0.0446***	0.0494***	0.0816***	0.0742***	0.0530***	0.0493***	0.0487***
	(0.004)	(0.004)	(0.007)	(0.006)	(0.006)	(0.006)	(0.003)
ln Age2	-0.00189***	-0.00196***	-0.00431***	-0.00361***	-0.00202***	-0.00220***	-0.00195***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln Age3			4.20e-05***	2.85e-05***			
			(0.000)	(0.000)			
ln Time	0.00137	-0.0529***	0.00184	-0.0493***	-0.0550***	-0.0480***	-0.0204***
	(0.002)	(0.005)	(0.002)	(0.005)	(0.006)	(0.006)	(0.003)
ln Time2		0.00156***		0.00146***	0.00162***	0.00140***	
		(0.000)		(0.000)	(0.000)	(0.000)	
1991	0.157***	-0.0711	0.145**	-0.0655	-0.0715	-0.071	-0.0027
	(0.060)	(0.058)	(0.059)	(0.057)	(0.058)	(0.058)	(0.056)
2009	-0.203***	-0.116***	-0.190***	-0.113***	-0.117***	-0.116***	-0.0109
	(0.038)	(0.035)	(0.037)	(0.035)	(0.035)	(0.035)	(0.038)
2010	-0.113***	-0.0365	-0.102***	-0.0333	-0.0376	-0.0364	-0.0183
	(0.037)	(0.034)	(0.036)	(0.034)	(0.034)	(0.034)	(0.040)
Trend Shift							-0.880***
							(0.111)
Trend Shift x Time							0.0476***
							(0.005)
MY Group x Age					-0.00101	-0.00405**	
					(0.001)	(0.002)	
MY Group x Age^2						0.000310***	
						(0.000)	
Observations	891	891	891	891	891	891	891
R2	0.731	0.776	0.742	0.781	0.776	0.778	0.777
R2 within	0.649	0.708	0.664	0.715	0.708	0.711	0.709
R2 between	0.802	0.511	0.885	0.698	0.507	0.670	0.499
sigma_u	0.067	0.099	0.050	0.082	0.102	0.086	0.100
sigma_e	0.216	0.197	0.211	0.195	0.197	0.197	0.197
rho	0.087	0.201	0.054	0.148	0.210	0.162	0.204
Corr(ui,xb)	0.322	0.303	0.301	0.311	0.310	0.376	0.299

Table 7-4 (continued): Estimation Results for Property Damage Only Crashes

Explanatory Variables	Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)						
	Model 8	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**

Constant (Model Years 1990-95)	7.927***	7.985***	7.862***	7.853***	7.848***	7.743***	7.765***
	(0.044)	(0.048)	(0.055)	(0.054)	(0.040)	(0.057)	(0.056)
MY 1996-97	0.181***	0.128***	0.259***	0.178***	0.165***	0.239***	0.162***
	(0.039)	(0.042)	(0.041)	(0.043)	(0.028)	(0.040)	(0.042)
MY 1998-2002	0.168***	0.117*	0.273***	0.204***	0.133***	0.247***	0.185***
	(0.061)	(0.062)	(0.062)	(0.063)	(0.043)	(0.062)	(0.061)
MY 2003-05	0.132*	0.0941	0.254***	0.220***	0.0904*	0.230***	0.204***
	(0.076)	(0.076)	(0.078)	(0.077)	(0.055)	(0.077)	(0.076)
MY 2006	0.154	0.126	0.299***	0.295***	0.11	0.272***	0.278***
	(0.095)	(0.095)	(0.097)	(0.095)	(0.073)	(0.097)	(0.095)
MY 2007	0.142	0.122	0.314***	0.334***	0.0955	0.281***	0.313***
	(0.102)	(0.102)	(0.105)	(0.103)	(0.076)	(0.105)	(0.103)
MY 2008-09	0.118	0.111	0.315***	0.366***	0.0734	0.272***	0.338***
	(0.101)	(0.100)	(0.105)	(0.103)	(0.070)	(0.104)	(0.103)
MY 2010	0.0465	0.0535	0.261**	0.342***	0.00609	0.212*	0.311***
	(0.114)	(0.114)	(0.118)	(0.117)	(0.086)	(0.117)	(0.117)
MY 2011-17	-0.0147	0.00349	0.197*	0.299***	-0.0336	0.148	0.268***
	(0.098)	(0.098)	(0.103)	(0.103)	(0.074)	(0.102)	(0.102)
MY 2018-19	-0.13	-0.13	0.0521	0.117	-0.1	0.0228	0.101
	(0.145)	(0.144)	(0.146)	(0.144)	(0.138)	(0.146)	(0.144)
ln Age	0.0509***	0.0475***	0.0994***	0.113***	0.0727***	0.0938***	0.109***
	(0.006)	(0.006)	(0.011)	(0.011)	(0.006)	(0.011)	(0.011)
ln Age2	-0.00199***	-0.00219***	-0.00439***	-0.00583***	-0.00354***	-0.00419***	-0.00574***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
ln Age3			3.76e-05***	5.45e-05***	2.75e-05***	3.51e-05***	5.31e-05***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln Time	-0.0208***	-0.0188***	-0.0584***	-0.0452***	-0.0188***	-0.0211***	-0.0170***
	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
ln Time2			0.00175***	0.00133***			
			(0.000)	(0.000)			
1991	-0.000815	-0.013	-0.0658	-0.0622	-0.000672	0.0126	-0.00511
	(0.057)	(0.057)	(0.057)	(0.056)	(0.056)	(0.056)	(0.055)
2009	-0.00947	-0.0209	-0.116***	-0.113***	-0.0144	-0.00558	-0.0267
	(0.038)	(0.038)	(0.034)	(0.034)	(0.038)	(0.038)	(0.037)
2010	-0.0172	-0.0237	-0.0376	-0.0352	-0.0162	-0.00873	-0.0173
	(0.040)	(0.040)	(0.034)	(0.033)	(0.040)	(0.040)	(0.039)
Trend Shift	-0.907***	-0.757***			-0.828***	-0.997***	-0.739***
	(0.129)	(0.137)			(0.111)	(0.129)	(0.134)
	0.0489***	0.0413***			0.0447***	0.0530***	0.0397***

Trend Shift x Time	(0.006)	(0.006)			(0.005)	(0.006)	(0.006)
MY Group x Age	-0.000604	-0.00404**	-0.00483***	-0.0130***		-0.00407**	-0.0128***
	(0.001)	(0.002)	(0.002)	(0.002)		(0.002)	(0.002)
MY Group x Age^2		0.000337***		0.000658***			0.000679***
		(0.000)		(0.000)			(0.000)
Observations	891	891	891	891	891	891	891
R2	0.777	0.779	0.783	0.791	0.781	0.783	0.791
R2 within	0.709	0.712	0.717	0.727	0.715	0.717	0.728
R2 between	0.497	0.685	0.529	0.344	0.678	0.675	0.417
sigma_u	0.101	0.084	0.110	0.115	0.083	0.103	0.107
sigma_e	0.197	0.196	0.194	0.191	0.195	0.194	0.191
rho	0.208	0.153	0.242	0.267	0.153	0.218	0.241
Corr(ui,xb)	0.309	0.381	0.207	0.175	0.307	0.249	0.203

7.1.11. Using the Models to Forecast

To simplify forecasting future rates for fatalities, non-fatal injuries, and involvement in property damage only crashes in the reference baseline alternative, we utilize the versions of each model that include fixed effects for safety cohorts, vehicle age and its squared value, the time trend measure (including any significant change in the trend), and where appropriate, indicator variables for recession years. As indicated previously, we use the coefficient estimates reported for Model 11 in Table 7-2, Table 7-3, and Table 7-4.

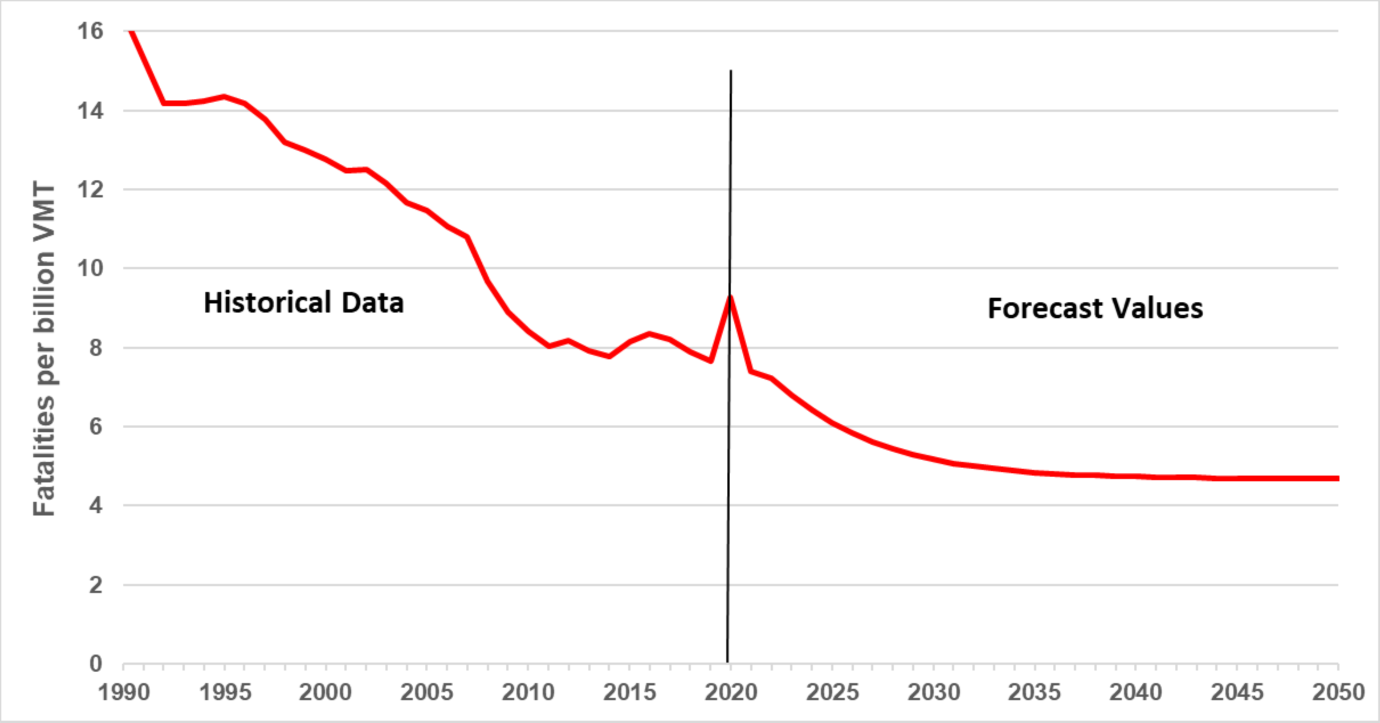
The process begins by estimating fatality, injury, and property damage crash involvement rates for new cars and light trucks that will be produced in future model years. Starting with the relevant rate for latest model year included in the estimation data when it was new (for example, the fatality rate for model year 2019 during calendar year 2019), we apply NHTSA's projections of the shares of new vehicles produced during each future model year that will be equipped with various crash avoidance technologies, the effectiveness of each technology in reducing specific crash "modes" (rollover, head-on, etc.), and the contribution of each crash mode to fatalities, injuries, or property damage. The following subchapter discusses the nature of these technologies, projects the shares of new vehicles that will be equipped with each of them and provides estimates of their effectiveness in preventing different crash modes and outcomes. This process generates forecasts of fatality, non-fatal injury, and property damage crash involvement rates for future model years during their initial year of use.

During each future calendar year, the appropriate new model year is assumed to be incorporated into the fleet and is represented by its projected rate of fatalities, injuries, and property damage per billion miles during its first year in use. At the same time, the rate for each earlier model year in the fleet is increased to reflect the effect of having aged an additional year, as calculated from the coefficients on the age-related variables in the relevant model historical. Any remaining vehicles originally produced during the model year that would have reached age 41 in a future calendar year are assumed to be retired from service and no longer contribute to the fleet's overall safety. Finally, the rates (again, fatality, non-fatal injury, or property damage) for these earlier model years are also adjusted downward to reflect continuation of their historical downward trends, which were estimated as part of the models discussed previously and thus control for both model year cohort effects and age.

This produces estimates of fatality, non-fatal injury, and property damage crash involvement rates for each model year making up the fleet during each future calendar year, and the process is continued until calendar year 2050. Multiplying these rates by the estimated number of miles driven by cars and light trucks of each model year in use during a future calendar year produces reference baseline estimates of total fatalities, non-fatal injuries, and cars and light trucks involved in property damage-only crashes.

Figure 7-4 illustrates the recent history and a forecast of the overall fatality rate for occupants of cars and light trucks. The sharp rise in the fatality rate for 2020 reflects the steep drop in car and light truck VMT during that year due to the COVID-19 pandemic and accompanying restrictions on activity, as well as an increase in fatalities that is not yet fully explained, but which may be due to riskier driving on less congested roadways.[1063] These rates are also used as the basis for estimating changes in safety resulting from reductions in the mass of new vehicles, additional rebound-effect driving, and changes in the numbers of cars and light trucks from different model years making up each calendar year's fleet. The underlying causes and methods for estimating each of those three sources of changes in safety are discussed in detail in various subchapters of this chapter.

Figure 7-4: Recent and Projected Future Fatality Rates for Cars and Light Trucks



Note: The abrupt rise in the fatality rate for 2020 shown in this figure reflects the large drop in car and light truck VMT during that year due to the COVID-19 pandemic and accompanying restrictions on activity, as well as a rise in fatalities.

7.2. Future Safety Trends Predicted by Advanced Safety Technologies

The model described so far uses trends observed over several decades to make a coarse projection of future safety rates. To augment these projections with knowledge about forthcoming safety improvements, the agency applied detailed empirical estimates of the market uptake and improving effectiveness of crash avoidance technologies to estimate their effect on the fleet-wide fatality rate, including explicitly incorporating both the direct effect of those technologies on the crash involvement rates of new vehicles equipped with them, as well as the "spillover" effect of those technologies on improving both the safety of occupants of vehicles that are not equipped with these technologies and other road uses use as pedestrians and cyclists.

[1063] NHTSA. 2021. 2020 Fatality Data Show Increased Traffic Fatalities During Pandemic. Risky Driving Behaviors Including Failure to Wear a Seatbelt, Speeding, and Drinking While Driving Identified as Contributing Factors. Available at: https://www.nhtsa.gov/press-releases/2020-fatality-data-show-increased-traffic-fatalities-during-pandemic. (Accessed: Feb, 16, 2024).

The development of advanced crash avoidance technologies in recent years indicates some level of safety improvement is almost certain to occur going forward. Moreover, autonomous vehicles offer the possibility of significantly reducing the effect of human perception, judgment or error in crash causation, a contributing factor in roughly 94 percent of all crashes. However, there is insufficient information and certainty regarding autonomous vehicles eventual impact to include them in this analysis.

Advanced technologies that are currently deployed or in development include:

1. **Forward Collision Warning (FCW)** systems passively assist drivers in avoiding or mitigating the impact of rear-end collisions (i.e., a vehicle striking the rear portion of a vehicle traveling in the same direction directly in front of it). FCW uses forward-looking vehicle detection capability, such as Radio Detection and Ranging (RADAR), Light Detection and Ranging (LIDAR) (laser), camera, etc., to detect other vehicles ahead and use the information from these sensors to warn the driver and to prevent crashes. FCW systems provide an audible, visual, or haptic warning, or any combination thereof, to alert the driver of an FCW-equipped vehicle of a potential collision with another vehicle or vehicles in the anticipated forward pathway of the vehicle.
2. **Crash Imminent Braking (CIB)** systems actively assist the drivers by mitigating the impact of rear-end collisions. These safety systems have forward-looking vehicle detection capability provided by sensing technologies such as RADAR, LIDAR, video camera, etc. CIB systems mitigate crash severity by automatically applying the vehicle's brakes shortly before the expected impact (i.e., without requiring the driver to apply force to the brake pedal).
3. **Dynamic Brake Support (DBS)** is a technology that actively increases the amount of braking provided to the driver during a rear-end crash avoidance maneuver. If the driver has applied force to the brake pedal, DBS uses forward-looking sensor data provided by technologies such as RADAR, LIDAR, video cameras, etc. to assess the potential for a rear-end crash. Should DBS ascertain a crash is likely (i.e., the sensor data indicate the driver has not applied enough braking to avoid the crash), DBS automatically intervenes. Although the way DBS has been implemented differs among vehicle manufacturers, the objective of the interventions is largely the same - to supplement the driver's commanded brake input by increasing the output of the foundation brake system. In some situations, the increased braking provided by DBS may allow the driver to avoid a crash. In other cases, DBS interventions mitigate crash severity.
4. **Pedestrian Automatic Emergency Breaking (PAEB)** systems provide automatic braking for vehicles when pedestrians are in the forward path of travel and the driver has taken insufficient action to avoid an imminent crash. Like CIB, PAEB safety systems use information from forward-looking sensors to automatically apply or supplement the brakes in certain driving situations in which the system determines a pedestrian is in imminent danger of being hit by the vehicle.
5. **Rear Automatic Braking** features are able to sense the presence of objects behind a reversing vehicle, alert the driver of the presence of the object(s) via auditory and visual alerts, and automatically engage the available braking system(s) to stop the vehicle.
6. **Semi-automatic Headlamp Beam Switching** devices provide either automatic or manual control of headlamp beam switching at the option of the driver. When the control is automatic, headlamps switch from the upper beam to the lower beam when illuminated by headlamps on an approaching vehicle and switch back to the upper beam when the road ahead is dark. When the control is manual, the driver may obtain either beam manually regardless of the conditions ahead of the vehicle.
7. **Lane Departure Warning (LDW)** is a driver assistance system that monitors lane markings on the road and alerts the driver when their vehicle is about to drift beyond a delineated edge line of their current travel lane.
8. **Lane Keep Assist (LKA)** utilizes LDW sensors to monitor lane markings but, in addition to warning the driver, provides gentle steering adjustments to prevent drivers from unintentionally drifting out of their lane.
9. **Lane Centering** keeps the vehicle centered in its lane and typically comes with steering assist to help the vehicle take gentle turns at highway speeds. These systems also work together with adaptive cruise control and lane keeping assist to give the car semi- autonomous capability.

10. **Blind Spot Detection (BSD)** systems use digital camera imaging technology or radar sensor technology to detect one or more vehicles in either of the adjacent lanes that may not be apparent to the driver. The system warns the driver of an approaching vehicle's presence to help facilitate safe lane changes.
11. **Lane Change Alert (LCA)** systems use digital camera imaging technology or radar sensor technology to detect vehicles either in, or rapidly approaching in adjacent lanes that may not be apparent to the driver. The system warns the driver of an approaching vehicle's presence to help facilitate safe lane changes.

7.2.1. Crash Avoidance Technologies

Beginning with the 2020 CAFE final rule, NHTSA augmented the sales-scrappage safety analysis with recent research into the effectiveness of specific advanced crash avoidance safety technologies (also known as ADAS or advanced driver assistance systems) that are expected to drive future safety improvement to estimate the impacts of crash avoidance technologies. The analysis analyzes seven crash avoidance technologies that are currently being produced and commercially deployed in the new vehicle fleet. These FCW, Automatic Emergency Braking (AEB),[1064] LDW, LKA, BSD, LCA, and PAEB. These are the principal technologies that are being developed and adopted in new vehicle fleets and will likely drive vehicle-based safety improvements for the coming decade. Manufactures are installing more of these ADAS technologies over time. Recent NHTSA actions on AEB and PAEB effectiveness further reinforce the adoption of these safety systems.[1065,1066] NHTSA notes that the terminology and the detailed characteristics of these systems may differ across manufacturers, but the basic system functions are generally similar.

These 7 technologies address four basic crash scenarios through warnings to the driver or alternately, through dynamic vehicle control:

1. Forward collisions, typically involving a crash into the rear of a stopped vehicle;
2. Lane departure crashes, typically involving inadvertent drifting across or into another traffic lane;
3. Blind spot crashes, typically involving intentional lane changes into unseen vehicles driving in or approaching the driver's blind spot;
4. Pedestrian crashes, usually involving frontal crashes where vehicles inadvertently impact pedestrians crossing a roadway.

Unlike traditional safety features where the bulk of the safety improvements were attributable to improved protection when a crash occurs (crash worthiness), the impact that ADAS will have on fatality and injury rates is a direct function of their effectiveness in preventing or reducing the severity of the crashes they are designed to mitigate. This effectiveness is typically measured using real world data comparing vehicles with these technologies to similar vehicles without them. While these technologies are actively being deployed in new vehicles, their penetration in the larger on-road vehicle fleet has been at a low but increasing level. This limits the precision of statistical regression analyses, at least until the technologies become more common in the on-road fleet.

NHTSA's approach to measuring these impacts is to derive effectiveness rates for these advanced crash-avoidance technologies from safety technology literature. NHTSA then applies these effectiveness rates to specific crash target populations for which the crash avoidance technology is designed to mitigate and adjusted to reflect the current pace of adoption of the technology, including the public commitment by manufactures to install these technologies. The products of these factors, combined across all 7 advanced technologies, produce a fatality rate reduction percentage that is applied to the fatality rate trend model discussed above, which projects both vehicle and non-vehicle safety trends. The combined model produces a projection of impacts of changes in vehicle safety technology as well as behavioral and infrastructural trends and produces a safety reference baseline from which impacts of the final standards can be examined.

[1064] AEB is a combination of CIB, DBS, and PEAB.
[1065] Automatic Emergency Braking Systems for Light Vehicles: Available at: https://www.regulations.gov/docket/NHTSA-2023-0021. (Accessed Feb. 16, 2024).
[1066] Heavy Vehicle Automatic Emergency Braking; AEB Test Devices: Available at: https://www.regulations.gov/docket/NHTSA-2023-0023. (Accessed Jan. 17, 2024).

Values for the effectiveness of advanced crash avoidance technologies ADAS are derived from studies focusing on light-duty vehicles. Comprehensive estimates for the effectiveness of these technologies for the HDPUV fleets do not exist. Furthermore, information on the installation rates for these technologies in HDPUV vehicles is not readily tabulated in Ward's. We assume that the installation rates of advanced crash avoidance technologies in the HDPUV vehicle fleet resembles that of the light-duty vehicle fleet. We assume the effectiveness rates of these technologies are comparable for both light-duty and HDPUV vehicles.

The reasons for these assumptions are the following. 1) The size of the light-duty vehicle fleet is much larger than the HDPUV vehicle fleet. This means that average effectiveness rates or technology installation rates for both groups combined would not change much if we possessed separate values. 2) The estimated effectiveness of advanced crash avoidance technologies come from a variety of different sized light-duty vehicles. The technology plausibly represents the average effectiveness of the technologies across vehicles of different masses. There is little evidence that vehicle mass determines whether or not crash avoidance technologies function effectively.[1067] Therefore, the estimated effectiveness values for light-duty vehicles can be applied to heavier HDPUV vehicles. 3) Manufacturers of light-duty vehicles are voluntarily applying advanced crash avoidance technologies on their light-duty vehicles. Many of these firms produce HDPUV vehicles and face similar consumer pressures to offer similar safety features on their larger vehicles. Therefore, it is plausible that the average installation rates of advanced crash avoidance technologies on light-duty vehicles will be comparable to the installation rates in HDPUV vehicles.

7.2.2. Technology Effectiveness Rates at Reducing Fatalities

7.2.2.1. Forward Crash Collision Technologies

For forward collisions, manufacturers are currently equipping vehicles with FCW and AEB. In anticipation of future standards, manufacturers have committed voluntarily to install some form of AEB on all light vehicles by the model year 2023 (September 2022).[1068] In May of 2023, NHTSA issued a proposed rule that would require all light-duty vehicles to be equipped with AEB and to meet certain performance standards. NHTSA finalized that rulemaking in 2024. Table 7-5 summarizes studies which have measured effectiveness for various forms of FCW and AEB over the past 13 years. Most studies focused on crash reduction rather than injury reduction. This is a function of limited injury data in the on-road fleet, especially during the early years of deployment of these technologies. In addition, it reflects engineering limitations in the technologies themselves. Initial designs of AEB systems were basically incapable of detecting stationary objects at speeds higher than 30 mph, making them potentially ineffective in higher speed crashes that are more likely to result in fatalities or serious injury. For example, Wiacek et al. (2-15) conducted a review of rear-end crashes involving a fatal occupant in the 2003-2012 NASS-CDS databases to determine the factors that contribute to fatal rear-end crashes.[1069] They found that the speed of the striking vehicle was the primary factor in 71 percent of the cases they examined. The average Delta-v of the striking vehicle in these cases was 46 km/h (28.5 mph), implying pre-crash travel speeds exceeding this speed. While Table 7-5 includes studies going back to 2005, the agency focused its attention on more recent studies conducted after 2012 to reflect more current safety systems and vehicle designs.

Table 7-5: Summary of Forward AEB Technology Effectiveness Estimates

Authors	AEB Type	Crashes	Fatalities	Injury Reduction		All Injuries
				Serious	Minor	

[1067] Vehicle mass does play an important role in determing whether a crash occurs and the potential severity of the crash. For example, a vehicle with a greater mass will require more force to avoid a frontal crash than a smaller vehicle in similar situations. Manufacturers design heavier vehicles with these distinctions in mind, and the ADAS systems leverage the design characteristics of the vehicle to ensure similar performance.
[1068] See https://www.nhtsa.gov/press-releases/nhtsa-iihs-announcement-aeb. Note that the agreement calls for CIB, but systems installed by manufacturers include various combinations of technologies that make up AEB.
[1069] Wiacek, C. et al. 2015. Real World Analysis of Fatal Rear-End Crashes. National Highway Traffic Safety Administration, *24th Enhanced Safety of Vehicles Conference.* 150270. Available at: https://www-esv.nhtsa.dot.gov/Proceedings/24/files/24ESV-000270.PDF. (Accessed: May 31, 2023).

Sugimoto & Sauer (2005)[1070]	CMBS	38%	44%			
Page et al. (2005)[1071]	EBA		7.50%			11%
Najm et al. (2005)[1072]	ACAS1073	6-15%				
Breuer et al. (2007)[1074]	BAS+1075	44%				
Kuehn et al. (2009)[1076]	CMBS	40.80%				
Grover et al. (2008)[1077]	AEB	30%				
Cicchino (2017)[1078]	FCW	27%				20%
	Low AEB	43%				45%
	High AEB	50%				56%
Kusano & Gabler (2012)[1079]	FCW	3.20%	29%	29%		
	AEB	7.70%	50%	50%		
Leslie et al. (2019)[1080]	FCW	21%				
	AEB	46%				
Spicer et al. (2021)[1081]	AEB	43%				
Leslie et al. (2021)[1082]	FCW	20%				
Leslie et al. (2021)	AEB	45%				

[1070] Sugimoto, Y.,Sauer, C. 2005. Effectiveness Estimation Method for Advanced Driver Assistance System and its Application to Collision Mitigation Brake systems. *19th International Technical Conference on the Enhanced safety of Vehicles (ESV)*: Washington D.C. June 6-9, 2005. pp. 05-148.
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[1072] Najm, W.G. et al. 2006. Evaluation of an Automotive Rear- End Collision Avoidance System (technical report DOT HS 810 569). John A. Volpe National Transportation System Center, U.S. Department of Transportation. Cambridge, MA.
[1073] Automotive Collision Avoidance System (ACAS).
[1074] Breuer, JJ. et al. 2007. Real world Safety Benefits of Brake Assistance Systems, Proceedings of the 20th International Technical Conference of the Enhanced Safety of Vehicles (ESV) in Lyon, France June 18-21, 2007. Available at: https://trid.trb.org/view/1364815. (Accessed: Feb. 16, 2024).
[1075] Brake Assistance Systems (BAS).
[1076] Keuhn, M. et al. 2009. Benefit Estimation of Advanced Driver Assistance Systems for Cars Derived from Real-World Accidents. Paper No. 09-0317. *21st International Technical Conference on the Enhanced Safety of Vehicles (ESV):* Stuttgart, Germany, June 15-18, 2009. Available at: https://www.researchgate.net/publication/267953383. (Accessed: Feb. 16, 2024).
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[1078] Cicchino, J.B. 2017. Effectiveness of Forward Collision Warning and Autonomous Emergency Braking Systems in Reducing Front-to-Rear Crash Rates. *Accident Analysis and Prevention.* Vol. 99(A): pp. 142–52. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0001457516304006?via%3Dihub. (Accessed: Feb. 16, 2024).
[1079] Kusano, K.D., Gabler, H.C. 2012. Safety Benefits of Forward Collision Warning, Brake Assist, and Autonomous Braking Systems in Rear-End Collisions. *IEEE Transactions on Intelligent Transportation Systems*. Vol. 13(4): pp. 1546-55. Available at: https://ieeexplore.ieee.org/abstract/document/6180219. (Accessed: Feb. 16, 2024).
[1080] Leslie, A. et al. 2019. Analysis of the Field Effectiveness of General Motors Production Active Safety and Advanced headlighting Systems. University of Michigan Transportation Research Institute, UMTRI-2019-6, Sept. 2019.
[1081] Spicer, R. et al. 2021. Effectiveness of Advanced Driver Assistance Systems in
Preventing System-Relevant Crashes. SAE Technical Paper 2021-01-0869, 2021. Available at: https://www.sae.org/publications/technical-papers/content/2021-01-0869/. (Accessed: Feb. 16, 2024).
[1082] Leslie, A. et al. 2021. Field Effectiveness of General Motors Advanced Driver Assistance and Headlighting Systems. *Accident Analysis & Prevention*. Vol. 159(2021). ISSN 0001-457575. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0001457521003067. (Accessed: Feb. 16, 2024).

Leslie et al. (2022)[1083]	AEB	40-45%				55-58%
Leslie et al. (2022)	FCW	20%				25%

Doecke et al. (2012) created simulations of 103 real world crashes and applied AEB system models with differing specifications to determine the change in impact speed that various AEB interventions might produce. Their modeling found significant rear-end crash speed reductions with various AEB performance assumptions. In addition, they estimated a 29 percent reduction in rear-end crashes and that 25 percent of crashes over 10 km/h were reduced to 10 km/h or less.

Cicchino (2017) analyzed the effectiveness of a variety of forward collision mitigation systems including both FCW and AEB systems. Cicchino used a Poisson regression to compare rates of police-reported crashes per insured vehicle year between vehicles with these systems and the same models that did not elect to install them. The analysis was based on crashes occurring during 2010 to 2014 in 22 States and controlled for other factors that affected crash risk.

Cicchino found that FCW reduced all rear-end striking crashes by 27 percent and rear-end striking injury crashes by 20 percent, and that AEB functional at high speeds reduced these crashes by 50 and 56 percent, respectively. She also found that low speed AEB without driver warning reduced all crashes by 43 percent and injury crashes by 45 percent. She also found that even low-speed AEB could impact crashes at higher speed limits. Reductions were found of 53 percent, 59 percent, and 58 percent for all rear-end striking crash rates, rear-end striking injury crash rates, and rear-end third party injury crash rates, respectively, at speed limits of 40-45 mph. For speed limits of 35 mph or less, reductions of 40 percent, 40 percent, and 43 percent were found. For speed limits of 50 mph or greater, reductions of 31 percent, 30 percent, and 28 percent, were found. Further, Cicchino (2016) found significant reductions (30 percent) in rear- end injury crashes even in crashes on roadways where speed limits exceeded 50 mph.

Kusano and Gabler (2012) examined the effectiveness of various levels of forward collision technologies including FCW and AEB based on simulations of 1,396 real world rear end crashes from 1993-2008 NASS CDS databases. The authors developed a probability-based framework to account for variable driver responses to the warning systems. Kusano and Gabler found FCW systems could reduce rear-end crashes by 3.2 percent and driver injuries in rear-end crashes by 29 percent. They also found that full AEB systems with FCW, pre-crash brake assist, and autonomous pre-crash braking could reduce rear-end crashes by 7.7 percent and reduce moderate to fatal driver injuries in rear-end crashes by 50 percent.

Fildes et al. (2015) performed meta-analyses to evaluate the effectiveness of low-speed AEB technology in Passenger Vehicles (PV) based on real-world crash experience across six different predominantly European countries. Data from these countries was pooled into a standard analysis format and induced exposure methods were used to control for extraneous effects. The study found a 38 percent overall reduction in rear-end crashes for vehicles with AEB compared to similar vehicles without this technology. The study also found no statistical evidence for any difference in effectiveness between urban roads with speed limits less than or equal to 60 km/h, and rural roads with speed limits greater than 60 km/h. Fildes et al. (2015) found no statistical difference in the performance of AEBs on lower speed urban or higher speed rural roadways.

Kusano and Gabler (2015) simulated rear-end crashes based on a sample of 1,042 crashes in the 2012 NASS-CDS. Modelling was based on 54 model year 2010-2014 vehicles that were evaluated in NHTSA's New Car Assessment Program (NCAP). Kusano and Gabler found FCW systems could prevent 0-67 percent of rear-end crashes and 2-69 percent of serious to fatal driver injuries.

Spicer et al. (2021) focused on ADAS technology effectiveness in 2.3 million Toyota vehicle crashes linked to 308,490 police reported crashes from 2015-2018. They used Cox proportional hazard regression modeling to

[1083] Leslie, A, et al. 2022. Analysis of the Field Effectiveness of General Motors Model Year 2013-2020 Advanced Driver Assistance System Features. University of Michigan Transportation Research Institute, UMTRI-2022-2. Available at: https://deepblue.lib.umich.edu/bitstream/handle/2027.42/171916/UMTRI-2022-2.pdf. (Accessed:Feb. 16, 2024).

measure the effectiveness of various ADAS technologies. The authors find that AEB in Toyota vehicles led to statistically significant reductions in front to rear crashes of 43 percent.

Leslie et al. (2019) analyzed the relative crash performance of 123,377 General Motors (GM) model year 2013 to 2017 vehicles linked to State police-reported crashes by VIN. GM provided VIN- linked safety content information for these vehicles to enable precise identification of safety technology content. The authors analyzed the effectiveness of a variety of crash avoidance technologies including both FCW and AEB separately. They estimated effectiveness comparing system-relevant crashes to baseline (control group) crashes using a quasi-induced exposure method in which rear-end struck crashes are used as the control group. Leslie et al. found that FCW reduced rear-end striking crashes of all severities by 21 percent, and that AEB (which includes FCW) reduced these crashes by 46 percent.[1084]

Leslie et al. (2021) expanded their previous analyses of relative crash performance. They linked data for 8,311,707 GM model year 2013-2019 with 424,972 State police crash reports. They analyzed the effectiveness of FCW AEB and PAEB. The authors found that FCW reduces rear-end struck crashes by 20 percent and radar based AEB reduces rear-end struck crashes by 45 percent, and camera based AEB reduced such crashes by 38%. Leslie et al. (2022) used 10.9 million GM MR 2013-2020 vehicles matched to 635,712 police reported crashes in 14 states through VINs. The authors find that FCW reduces rear-end struck crashes by 20 percent and radar based AEB reduces rear-end struck crashes by 45 percent. Camera based AEB reduces such crashes by 40 percent. The weighted average of these two AEB systems based on crash frequency is approximately 41.49 percent.

For this analysis, NHTSA based its projections for all technologies except PAEB on Leslie et al. (2019) since the report contains confidence bounds applicable for lower and upper bound sensitivity analyses. Subsequent iterations of their University of Michigan Transportation Research Institute (UMTRI) report omit this information and only provides point estimates of coefficient values. Apart from PAEB, the estimated effectiveness of advanced crashed avoidance technologies does not change substantially in subsequent reports. Furthermore, Leslie et al. are the only studies to report estimates for each of the six crash avoidance technologies analyzed for the final rule, hence providing a certain level of consistency amongst estimates. NHTSA recognizes that there is uncertainty in estimates of these technologies' effectiveness, especially at this early stage of deployment. For this reason, the agency examines a range of effectiveness rates to estimate boundary outcomes in a sensitivity analysis.

Leslie et al. (2019) measured effectiveness against all categories of crashes but did not specify effectiveness against crashes that result in fatalities or injuries. NHTSA examined a range of effectiveness rates against fatal crashes using a baseline based on boundary assumptions of no effectiveness and full effectiveness across all crash types. Our baseline is thus a simple average of these two extremes. Sensitivity cases were based on the 95th percent confidence intervals calculated from this baseline. Leslie et al. found effectiveness rates of 21 percent for FCW and 46 percent for AEB. Our central fatality effectiveness estimates will thus be 10.5 percent for FCW and 23 percent for AEB. The calculated 95th percentile confidence limits range is 8.11 to 12.58 percent effective for FCW and 20.85 to 25.27 for AEB. We note that our central estimate is conservative compared to averages of those studies that did specifically examine fatality impacts; that is, the analysis assumes reduced future fatalities less than most of, or the average of, those studies, and thus minimizes the estimate of fatality impacts under alternatives to the current standards. Furthermore, we note that the estimate against fatal crashes is higher in the recent studies in Table 7-5, which reflects our

[1084] NHTSA notes that UMTRI, the sponsoring organization for the Leslie et al. study, published a previous version of this same study utilizing the same methods in March of 2018 (Flannagan, C. and Leslie, A, Crash Avoidance Technology Evaluation Using Real-World crashes, University of Michigan Transportation Research Institute, March 22, 2018). The agency focused on the more recent 2019 study because its sample size is significantly larger, and it represents more recent model year vehicles. The revised (2019) study uses the same basic techniques but incorporated a larger database of system-relevant and control cases (123,377 cases in the 2019 study vs. 35,401 in the 2018 study). Relative to the Flannagan and Leslie (2018) findings, the results of the 2019 study varied by technology. The revised study found effectiveness rates of 21 percent for FCW and 46 percent for AEB, compared to 16 and 45 percent in the 2018 study. The revised study found effectiveness rates of 10 percent for LDW and 20 percent for LKA, compared to 3 and 30 percent for these technologies in the 2018 study. The revised study found effectiveness rates of 3 percent for BSD and 26-37 percent for LCA systems, compared to 8 percent and 19-32 percent for these technologies in the 2018 study. Thus, some system effectiveness estimates increased while others decreased.

understanding that earlier iterations of AEB and FCW may have been less effective against crashes that result in fatalities than newer and improved versions.[1085]

7.2.2.2. Pedestrian Crash Avoidance Technologies

Table 7-6: Summary of Pedestrian AEB Technology Effectiveness Estimates

Authors	AEB Type	Crash Reduction	Injury Reduction	Fatality/ Serious Injury Reduction
Yanagisawa et al. (2017). NHTSA Report No. DOT HS 812 400.	PAEB		91%-96.5%**	
IIHS/Cicchino (2022)[1086]	PAEB	25-27%	29-30%	3%*
Leslie et al. (2021)[1087]	PAEB	14%*		
Leslie et al. (2022)[1088]	PAEB	23%		
PARTS Summary Report DRAFT (2022)	PAEB		4%*	2%*
Spicer et al. (2021)[1089]	PAEB	16%		
*not statistically significant, ** low speed, daylight, head on crashes				

Yanagisawa, Swanson, Azeredo, and Najm (2017) used simulation studies to estimate the effectiveness of PAEB technologies. They focused on two scenarios, the first is a frontal collision with a pedestrian crossing the road and the second with a vehicle going straight and the pedestrian moving parallel to the vehicle. These crashes simulations represent a subset of potential situations where PAEB might be deployed.

Spicer et al. (2021) focused on ADAS technology effectiveness in 2.3 million Toyota vehicle crashes linked to 308,490 police reported crashes from 2015-2018. They used Cox proportional hazard regression modeling to measure the effectiveness of various ADAS technologies. The authors did not find a statistically significant reduction in pedestrian crashes with PAEB. The point estimate is 16 percent and the 95% confidence interval ranges from a 31 percent reduction to 4 percent increase in pedestrian crashes.

Leslie et al. (2021) expanded upon their previous analyses of relative crash performance. They utilized a hazard model to study the effectiveness of various safety technologies on General Motors vehicles' crash avoidance. They linked data for 8,311,707 GM model year 2013-2019 with 424,972 State police crash reports. They analyzed the effectiveness of FCW, AEB and PAEB. The effectiveness of PAEB was statistically insignificant, and the point estimate of the effect on front pedestrian crash incidences is a 14 percent reduction.

Leslie et al. (2022) used 10.9 million GM MR 2013-2020 vehicles matched to 635,712 police reported crashes in 14 states through VINs. The most notable result was the first statistically significant observed reduction in frontal pedestrian crashes from PAEB in a quasi-induced exposure analysis. With respect to pedestrians and other vulnerable road uses the authors found that frontal pedestrian breaking reduced the incidence rate of pedestrian crashes by 23 percent. This was due in part to many GM vehicles adopting PAEB technologies in

[1085] As an example of improvements, NHTSA notes that the Mercedes system described in their 2015 owner's manual specified that for stationary objects the system would only work in crashes below 31 mph, but that in their manual for the 2019 model, the systems are specified to work in these crashes up to 50 mph.
[1086] Cicchino, J. B. 2022. Effects of Automatic Emergency Braking Systems Pedestrian Crash Risk. *Accident Analysis & Prevention*,. 172, (106686). Available at: https://www.sciencedirect.com/science/article/abs/pii/S0001457522001221?via%3Dihub. (Accessed: Feb. 16, 2024).
[1087] Leslie, A. et al. 2021. Field Effectiveness of General Motors Advanced Driver Assistance and Headlighting Systems. *Accident Analysis & Prevention.* Vol. 159(2021). ISSN 0001-457575. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0001457521003067. (Accessed: Feb. 16, 2024).
[1088] Leslie, A, et al. 2022. Analysis of the Field Effectiveness of General Motors Model Year 2013-2020 Advanced Driver Assistance System Features. University of Michigan Transportation Research Institute, UMTRI-2022-2. Available at: https://deepblue.lib.umich.edu/bitstream/handle/2027.42/171916/UMTRI-2022-2.pdf. (Accessed: Feb. 16, 2024).
[1089] Spicer, R. et al. 2021. Effectiveness of Advanced Driver Assistance Systems in Preventing System-Relevant Crashes. SAE Technical Paper 2021-01-0869, 2021. Available at: https://www.sae.org/publications/technical-papers/content/2021-01-0869/. (Accessed: Feb. 16, 2024).

model year 2020. Another finding was that IntelliBeam/automatic high beam headlights reduce vulnerable road user collisions by 22 percent during nighttime conditions.[1090]

IIHS/Cicchino (2022) focused on the effectiveness of PAEB on crash incidence, crashes with injury, and crashes with severe injury/death. The underlying data was linked data from the Highway Loss Data Institute matched with police reported crashes via VINs for model year 2017-2020. The research used both logistic and Poisson regression models for quasi-induced exposure, the author found comparable results. PAEB installation reduced pedestrian crashes by 25-29 percent and crashes with pedestrian injury by 29-30 percent. The author did not find a statistically significant result, but the point estimates suggested a 3-29 percent reduction in fatalities/severe injury. The author did not find clear evidence that PAEB reduced pedestrian deaths due to low statistical power. The author also found little evidence that PAEB systems were effective in low light conditions, when turning, or when speeds exceeded 50 mph.

The values for PAEB effectiveness used in the CAFE Model for fatalities are derived from the values used in draft PAEB/AEB Rulemaking (FRIA) in 2023. The effectiveness value for PAEB on fatalities in the final rule is 39 percent. The estimate of 39 percent effectiveness was found by applying findings from PAEB test track data and pedestrian collision data to engineering-based assumptions on vehicle braking performance in the presence of pedestrians in conflict with vehicle paths.[1091] The engineering-based assumptions were specified conditionally on the performance requirements of the PAEB/AEB rulemaking, reflecting strong assumed performance in collisions where pedestrians travel along a vehicle's path, weaker performance in collisions where pedestrians travel across a vehicle's path, and no improvement above baseline for other pedestrian collisions. The estimate of 39 percent effectiveness was applied in this analysis because empirical studies have lacked the statistical power to clearly identify precise PAEB effectiveness. The FRIA will provide a baseline value for PAEB effectiveness on systems used in the future and serves as a lower bound for future PAEB effectiveness.

7.2.2.3. Lane Departure Crash Technologies

For lane departure crashes, manufacturers are currently equipping vehicles with LDW, as well as LKA, which provides gentle steering adjustments to help drivers avoid unintentional lane crossing. Table 7-7 summarizes studies which have measured effectiveness for LDW and LKA.

Table 7-7: Summary of LDW Technology Effectiveness Estimates

Authors	LDW Type	Crash Reduction	Fatalities	Injury Reduction		All Injuries
				Serious	Minor	
Cicchino (2018)[1092]	LDW	11%				21%
Sternlund, Strandroth, et al. (2017)[1093]	LDW/LKA					6-30%
Leslie et al. (2019)[1094]	LDW	10%				
	LKA	20%				
Kusano & Gabler (2015)[1095]	LDW	11-23%	13-22%	13-22%		

[1090] The majority of night time vulnerable road user collisions are derived from animal strikes. Animals were used as a proxy for pedestrians or cyclists. A separate analysis focusing only on pedestrians results in a statistically insignificant reduction of 24%.
[1091] Pedestrian crashes are more likely to result in death than other crash types and this suggests that many pedestrian crashes that intially result in severe injury also eventually result in death. A such this analysis uses an effectiveness measure that incorporates information on crashes involving serious injury as most representative, yielding the 39% effectiveness value from the PAEB/AEB Rulemaking (FRIA). *Memorandum and "Light Vehicle AEB FRIA"* https://www.regulations.gov/document/NHTSA-2023-0021-1069 (Accessed May 20, 2024), p.290.
[1092] Cicchino, J.B. 2018. Effects of Lane Departure Warning on Police-Reported Crash Rates. *Journal of Safety Research*. Vol. 66 (2018): pp.61-70. National Safety Council and Elsevier Ltd., May, 2018. Available at: https://pubmed.ncbi.nlm.nih.gov/30121111. (Accessed: Feb. 16, 2024).
[1093] Sternlund, S. et al. 2017. The Effectiveness of Lane Departure Warning Systems – A Reduction in Real-World Passenger Car Injury Crashes. *Traffic Injury Prevention*. Vol. 18(2). Available at: https://pubmed.ncbi.nlm.nih.gov/27624313. (Accessed: Feb. 16, 2024).
[1094] Leslie et al. (2019), op. cit.
[1095] Kusano and Gabler (2015), op. cit.

Kusano, Gorman, et al. (2014)[1096]	LDW	29%		24%		
Spicer et al. (2021)[1097]	LKA	4-9%				
Spicer et al. (2021)	LDW	4%				
Leslie et al. (2022)[1098]	LDW	10-12%				
Leslie et al. (2022)	LKA	9-16%				
Leslie et al. (2022)[1099]	LDW	4-8%				
Leslie et al. (2022)	LKA	8-17%				

Cicchino (2018) examined crash involvement rates per insured vehicle year for vehicles that offered LDW as an option and compared crash rates for those that had the option installed to those that did not. The study focused on single-vehicle, sideswipe, and head-on crashes as the relevant target population for LDW effectiveness rates. The study examined 5,433 relevant crashes of all severities found in 2009-2015 police-reported data from 25 States. The study was limited to crashes on roadways with 40 mph or greater speed limits not covered in ice or snow since lower travel speeds would be more likely to fall outside of the LDW systems' minimum operational threshold. Cicchino found an overall reduction in relevant crashes of 11 percent for vehicles that were equipped with LDW. She also found a 21 percent reduction in injury crashes. The result for all crashes was statistically significant, while that for injury crashes approached significance ($p<0.07$). Cicchino did not separately analyze LKA systems.

Sternlund et al. (2017) studied single vehicle and head-on injury crash involvements relevant to LDW and LKA in Volvos on Swedish roadways. They used rear-end crashes as a control and compared the ratio of these two crash groups in vehicles that had elected to install LDW or LKA to the ratio in vehicles that did not have this content. The studied crashes were limited to roadways with speeds of 70-120 kph and not covered with ice or snow. Sternlund et al. found that LDW/LKA systems reduced single vehicle and head-on injury crashes in their crash population by 53 percent, with a lower limit of 11 percent, which they determined corresponded to a reduction of 30 percent (lower limit of 6 percent) across all speed limits and road surface assumptions.

Spicer et al. (2021) focused on ADAS technology effectiveness in 2.3 million Toyota vehicle crashes linked to 308,490 police reported crashes from 2015-2018. They used Cox proportional hazard regression modeling to measure the effectiveness of various ADAS technologies. Generally, LDW and LKA in Toyota vehicles failed to result in statistically significant reductions in their targeted crashes. The only statistically signific crash reduction attributable to LKA was run-off roadway crashes, a point estimate of 9 percent with a 95% confidence interval of 1-16 percent.

Leslie et al. (2019) analyzed the relative crash performance of 123,377 General Motors (GM) model year 2013 to 2017 vehicles linked to state police-reported crashes by VIN. GM provided VIN- linked safety content information for these vehicles to enable precise identification of safety technology content. The authors analyzed the effectiveness of a variety of crash avoidance technologies including both LDW and LKA separately. They estimated effectiveness comparing system-relevant crashes to baseline (control group) crashes using a quasi-induced exposure method in which rear-end struck crashes are used as the control group. Leslie et al. found that LDW reduced lane departure crashes of all severities by 10 percent, and that LKA (which includes LDW) reduced these crashes by 20 percent.

[1096] Kusano, K. et al. 2014. Potential Occupant Injury Reduction in the U.S. Vehicle Fleet for Lane Departure Warning-Equipped Vehicles in Single-Vehicle Crashes. *Traffic Injury Prevention* 2014(15) Suppl 1:S157-64. Available at: https://pubmed.ncbi.nlm.nih.gov/25307382/. (Accessed: Feb. 16, 2024).
[1097] Spicer, R. et al. 2021. Effectiveness of Advanced Driver Assistance Systems inPreventing System-Relevant Crashes. SAE Technical Paper 2021-01-0869. Available at: https://www.sae.org/publications/technical-papers/content/2021-01-0869/. (Accessed: Feb. 16, 2024).
[1098] Leslie, A. et al. 2021. Field Effectiveness of General Motors Advanced Driver Assistance and Headlighting Systems. *Accident Analysis & Prevention.* Vol. 159(2021). ISSN 0001-457575. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0001457521003067. (Accessed: Feb. 16, 2024).
[1099] Leslie, A, et al. 2022. Analysis of the Field Effectiveness of General Motors Model Year 2013-2020 Advanced Driver Assistance System Features. University of Michigan Transportation Research Institute, UMTRI-2022-2. Available at: https://deepblue.lib.umich.edu/bitstream/handle/2027.42/171916/UMTRI-2022-2.pdf. (Accessed: Feb. 16, 2024).

Leslie et al. (2022) used 10.9 million GM MR 2013-2020 vehicles matched to 635,712 police reported crashes in 14 states through VINs. They disaggregated the effects of LDW and LKA based on types of crashes, opposite direction, same direction, and off-road crash types. For crashes for vehicles traveling in the same direction, LDW reduced incidents by 4 percent and LKA by 10 percent. There was no statistically significant reduction in crashes for vehicles travelling in opposite directions (point estimates for LDW and LKA were 5 and 8 percent reductions). For road departure crashes, LCA reduced incidents by 8 percent and LKA by 17 percent. The average observed weighted effectiveness of LCA reducing crashes was a 6.99 percent. For LKA the reduction was 14.76 percent.

Kusano et al. (2014) developed a comprehensive crash and injury simulation model to estimate the potential safety impacts of LDW. The model simulated results from 481 single-vehicle collisions documented in the NASS-CDS database for the year 2012. Each crash was simulated as it actually occurred and again as it would occur had the vehicles been equipped with LDW. Crashes were simulated multiple times to account for variation in driver reaction, roadway, and vehicle conditions. Kusano et al. found that LDW could reduce all roadway departure crashes caused by the driver drifting from his or her lane by 28.9 percent, resulting in 24.3 percent fewer serious injuries.

Kusano and Gabler (2015), simulated single-vehicle roadway departure crashes based on a sample of 478 crashes in the 2012 NASS-CDS. Modelling was based on 54 model year 2010- 2014 vehicles that were evaluated in NHTSA's NCAP. Kusano and Gabler found LDW systems could prevent 11-23 percent of drift-out-of-lane crashes and 13- 22 percent of serious to fatally injured drivers.

As noted previously for frontal crash technologies, we will base our projections on Leslie et al. (2019). However, unlike forward crash technologies, lane change technologies are operational at travel speeds where fatalities are likely to occur. Both LDW and LKA typically operate at speeds above roughly 35 mph. For this reason, and because the research noted in Table 7-7 indicates similar effectiveness against fatalities, injuries, and crashes, we believe it is reasonable to assume the Leslie et al. crash reduction estimates are generally applicable to all crash severities, including fatal crashes. Our central effectiveness estimates are thus 10 percent for LDW and 20 percent for LKA. For sensitivity analysis, we adopt the 95 percent confidence intervals from Leslie et al. For LKA this range is 14.95-25.15 percent. For LDW, the upper range was 4.95-13.93 percent.

7.2.2.4. Blind Spot Crash Technologies

To address blind spot crashes, manufacturers are currently equipping vehicles with BSD and the more advanced version of this, LCA. Table 7-8 summarizes studies which have measured effectiveness for BSD and LCA.

Table 7-8: Summary of BSD Technology Effectiveness Estimates

Authors	BSD Type	Crash Reduction	Injury Reduction
Cicchino (2017b)[1100]	BSD	14%	23%
Leslie et al. (2019)[1101]	BSD	3%	
	LCA	26%	
Isaksson-Hellman & Lindman (2018)1102	LCA	30%*	31%**

[1100] Cicchino, J.B. 2018. Effects of Blind Spot Monitoring Systems on Police-Reported Lane-Change Crashes. *Traffic Injury Prevention.* Vol. 19(6): pp. 615-22. Available at: https://www.tandfonline.com/doi/full/10.1080/15389588.2018.1476973?scroll=top&needAccess=true&role=tab. (Accessed: Feb. 16, 2024).
[1101] Leslie et al. (2019), op. cit.
[1102] Isaksson-Hellman, I., Lindman, M. 2018. An Evaluation of the Real-World Safety Effect of a Lane Change Driver Support System and Characteristics of Lane Change Crashes Based on Insurance Claims. *Traffic Injury Prevention.* Vol.19(supp. 1). Available at: https://pubmed.ncbi.nlm.nih.gov/29584482. (Accessed: Feb. 16, 2024).

Spicer et al. (2021)[1103]	BSD	4%	
Leslie et al. (2022)[1104]	LCA	26%	
Leslie et al. (2022)	BSD	7%	
* Reduction in claim costs across all lane change crashes			
** Reduction in severe crashes with repair costs greater than $1250			

Cicchino (2017) used Poisson regression to compare crash involvement rates per insured vehicle year in police-reported lane-change crashes in 26 U.S. States during 2009-2015 between vehicles with blind spot monitoring and the same vehicle models without the optional system, controlling for other factors that can affect crash risk. Systems designs across the 10 different manufacturers included in the study varied regarding the extent to which the size of the adjacent lane zone that they covered exceeded the blind spot area, speed differentials at which vehicles could be detected, and their ability to detect rapidly approaching vehicles, but these different systems were not examined separately. The study examined 4,620 lane change crashes, including 568 injury crashes. Cicchino found an overall reduction of 14 percent in blind spot related crashes of all severities, with a non-significant 23 percent reduction in injury crashes.

Spicer et al. (2021) focused on ADAS technology effectiveness in 2.3 million Toyota vehicle crashes linked to 308,490 police reported crashes from 2015-2018. They used Cox proportional hazard regression modeling to measure the effectiveness of various ADAS technologies. The authors do not find a statistically significant reduction in sideswipe crashes in the same direction in vehicles with BSD. The point estimate is 4 percent.

Leslie et al. (2019) analyzed the relative crash performance of 123,377 2013-2017 General Motors (GM) vehicles linked to State police-reported crashes by VIN. GM provided VIN-linked safety content information for these vehicles to enable precise identification of safety technology content. The authors analyzed the effectiveness of a variety of crash avoidance technologies including both BSD and LCA separately. They estimated effectiveness comparing system-relevant crashes to baseline (control group) crashes using a quasi-induced exposure method in which rear-end struck crashes are used as the control group. Flannagan and Leslie found that BSD reduced lane departure crashes of all severities by 3 percent (non-significant), and that LCA (which includes BSD) reduced these crashes by 26 percent.

Leslie et al. (2022) used 10.9 million GM MR 2013-2020 vehicles matched to 635,712 police reported crashes in 14 states through VINs. For BSD they found the technology reduces crash incidents by 8 percent (non-significant). For LCA inclusive of BSD, the authors find these technologies reduce only 16% of target crashes.

Isaksson-Hellman and Lindman (2018) evaluated the effect of the Volvo Blind Spot Information System (BLIS) on lane change crashes. Volvo's BLIS functions as an LCA, detecting vehicles approaching the blind spot as well as those already in it. The authors analyzed crash rate differences in lane change situations for cars with and without the BLIS system based on a population of 380,000 insured vehicle years. The authors found the BLIS system did not significantly reduce the overall number of lane change crashes of all severities, but they did find a significant 31 percent reduction in crashes with a repair cost exceeding $1250, and a 30 percent lower claim cost across all lane change crashes, indicating a reduced crash severity effect.

Like lane change technologies, blind spot technologies are operational at travel speeds where fatalities are likely to occur. NHTSA therefore assumes the Leslie et al. (2019) crash reduction estimates are generally applicable to all crash severities, including fatal crashes. Our central effectiveness estimates are thus 3 percent for BSD and 26 percent for LCA. For sensitivity analysis, we adopt the 95 percent confidence intervals from Leslie et al. For LCA this range is 16.59-33.74 percent. For BSD, the upper range was 14.72 percent, but the findings were not statistically significant. The agency therefore limited the range to 0-14.72

[1103] Spicer, R. et al. 2021. Effectiveness of Advanced Driver Assistance Systems in Preventing System-Relevant Crashes. SAE Technical Paper 2021-01-0869. Available at: https://www.sae.org/publications/technical-papers/content/2021-01-0869/. (Accessed: Feb. 16, 2024).
[1104] Leslie, A. et al. 2022. Analysis of the Field Effectiveness of General Motors Model Year 2013-2020 Advanced Driver Assistance System Features. University of Michigan Transportation Research Institute, UMTRI-2022-2. Available at: https://deepblue.lib.umich.edu/bitstream/handle/2027.42/171916/UMTRI-2022-2.pdf. (Accessed: Feb. 16, 2024).

percent. Table 7-8 summarizes the effectiveness rates calculated in Leslie et al. (2019) and used in this analysis. Differences between the rates listed as "Used in CAFE Fatality Analysis" and those computed from Leslie et al. (2019) are explained in the above discussion.

Table 7-9 summarizes the effectiveness rates established in the literature and the rates we will use to analyze each technology's impact on fatalities.

Table 7-9: Summary of Advanced Technology Effectiveness Rates for Central and Sensitivity Cases

Tech.			Effectiveness values			Used in CAFE Fatality Analysis		
	Estimate	Std. Error	Central	Low	High	Central	Low	High
FCW[a]	-0.2334	0.0288	21	16.22	25.16	10.5	8.11	12.58
AEB[a]	-0.6218	0.0419	46	41.71	50.54	23	20.85	25.27
LDW[a]	-0.1004	0.0253	10	4.95	13.93	10	4.95	13.93
LKA[a]	-0.2258	0.0326	20	14.95	25.15	20	14.95	25.15
BSD[a]	-0.0297	0.0661	3	-10.50	14.72	3	0.00	14.72
LCA[a]	-0.2965	0.0587	26	16.59	33.74	26	16.59	33.74
PAEB[b]	-0.3900	-	17.14	3.42	28.04	17.14	3.42	28.04

[a] Leslie et al. 2017/UMTRI September 2019 Report
[b] PAEB AEB Rulemaking PRIA (2023)

7.2.3. Technology Effectiveness Rates at Reducing Non-fatal and PDO Crashes

The same data and methods to compute the impact of advanced crash avoidance technologies on fatalities are used to examine the effectiveness of these technologies against non-fatal and PDO crashes. Effectiveness for crash types were derived as averages for all crash types, and it is thus reasonable to apply them to both injury and PDO crashes. We assume effectiveness numbers for FCW for avoiding injury and PDOs to be 21% in both cases. Similarly, for AEB we use an effectiveness value of 46% for injury avoidance and for PDO. Effectiveness rates against nonfatal injuries and PDOs for the two lane-change and blind spot technologies are shown in Table 7-13 and Table 7-14. For the two frontal impact technologies, the central effectiveness rate noted in Table 7-12 was used rather than the reduced rates that were applied against fatalities. That is, we assume that effectiveness against crashes is a reasonable proxy for effectiveness against nonfatal injuries and PDOs. The percentages of target population applicable to these crashes were taken from Wang (2019) using results specific to these types of crashes.

7.2.4. Target Population for Crash Avoidance Technologies

The impact these technologies will have on safety is a function of both their effectiveness rate and the portion of occupant fatalities that occur under circumstances that are relevant to the technologies function. NHTSA based target population estimates on a recent study that examined these portions specifically for a variety of crash avoidance technologies. Wang (2019)[1105] documented target populations for five groups of collision avoidance technologies in PVs including forward collisions, lane keeping, blind zone detection, forward pedestrian impact, and backing collision avoidance. The first three of these affect the light vehicle occupant target population examined in this analysis. Wang separately examined crash populations stratified by severity including fatal injuries, non-fatal injuries, and PDO vehicles. Wang based her analysis on 2011-2015 data from NHTSA's FARS, National Automotive Sampling System (NASS), and GES. FARS data were the basis for fatal crashes while nonfatal injuries and PDOs were derived from the NASS and GES. Wang followed the pre-crash typology concept initially developed by Volpe.[1106] Under this concept, crashes are categorized into mutually exclusive and distinct scenarios based on vehicle movements and critical events

[1105] Wang, J.S. 2019. Target Crash Population for Crash Avoidance Technologies in PVs. Report No. DOT HS 812 653. National Highway Traffic Safety Administration: Washington, D.C. Available at: https://crashstats.nhtsa.gov/Api/Public/ViewPublication/812653. (Accessed: Feb. 16, 2024).
[1106] Najm, W. G. et al. 2007. Pre-Crash Scenario Typology for Crash Avoidance Research. Report No. DOT HS 810 767. National Highway Traffic Safety Administration: Washington, D.C.

occurring just prior to the crash. Table 7-10 summarizes the portion of total annual crashes and injuries for each crash severity category that is relevant to the three crash scenarios examined.

Table 7-10: Summary of Target Crash Proportions by Technology Group

Safety System Crash Type	Crashes	Fatalities	MAIS 1-5 Injuries	PDOVs
Frontal Crashes	29.4%	3.8%	31.5%	36.3%
Lane Departure Crashes	19.4%	44.3%	17.1%	11.9%
Blind Spot Crashes	8.7%	1.6%	6.7%	11.8%
Pedestrian Crashes	1.3%	15.6%	2.9%	

The relevant proportions vary significantly depending on the severity of the crash. The rear-end crashes that are addressed by FCW and AEB technologies tend to be low-speed crashes and thus account for a larger portion of non-fatal injury and PDO crashes than for fatalities. Only 4 percent of fatal crashes occur in front-to-rear crashes, but over 30 percent of nonfatal crashes are this type. By contrast, fatal crashes are highly likely to involve inadvertent lane departure, 44 percent of all light vehicle occupant fatalities occur in crashes that involve lane departure, but only 17 percent of non-fatal injuries and 12 percent of PDOs involve this crash scenario. Blind spot crashes account for only about 2 percent of fatalities, 7 percent of maximum abbreviated injury scale (MAIS) 1-5 injuries, and 12 percent of PDOs.

The target population of this analysis was previously occupants of light-duty vehicles subject to CAFE. We chose occupants of light-duty vehicles rather than a more inclusive group such as all road users—which would include pedestrians, bicyclists, and occupants of heavier vehicles—because the agency has been collecting data and developing statistical models for in-vehicle occupants for decades. For this analysis we have expanded the target population to include nonoccupants as well. Nonoccupants in frontal crashes are captured through a separate analysis of PAEB. For lane change and blind spot detection crashes, nonoccupants are an insignificant portion of crashes, and we retained the crash proportions we had developed for occupants. The values in Table 7-10 are portions of all crashes that occur annually. These include crashes of motor vehicles not subject to the current CAFE rulemaking such as medium and large trucks, buses, motorcycles, bicycles, etc. To adjust for this, the values in Wang are normalized to represent their portion of all light-duty passenger vehicle crashes, rather than all crashes of any type.

Wang provides total PV fatalities consistent with her technology numbers which are used as a baseline for this process. Based on 2011-2015 FARS data, Wang found an average of 29,170 PV occupant fatalities occurred annually. A second adjustment to Wang's results was made to make them compatible with the effectiveness estimates found in Leslie et al. In her target population estimate for LDW, Wang included both head-on collisions and rollovers, but Leslie et al. did not. The Leslie et al. (2019) effectiveness rate is thus applicable to a smaller target population than that examined by Wang. To make these numbers more compatible, counts for these crash types were removed from Wang's lane departure totals.

Electronic Stability Control (ESC) has been standard equipment in all light vehicles in the United States since the 2012 model year. ESC is highly effective in reducing roadway departure and traction loss crashes, and although it will be present in all future model year vehicles, it was present in only about 30 percent of the 2011-2015 on-road fleet examined by Wang. To reflect the impact of ESC on future on-road fleets therefore, NHTSA further adjusted Wang's numbers to reflect a 100 percent ESC presence in the on-road fleet. NHTSA allocated the reduced roadway departure fatalities to the LDW target population, and the reduced traction loss fatalities to the AEB target population. This has the effect of reducing the total fatalities in both groups as well as in the total projected fatalities baseline.

Table 7-11 summarizes the revised incidence counts and re-calculated proportions of total PV occupant crash/injury. Revised totals are derived from original totals referenced in Table 1-3 in Wang (2019).

Table 7-11: Adjusted Target Crash Counts and Proportions

Crash Type	Crashes	Fatalities	MAIS 1-5	PDOVs
Frontal Crashes	1,703,541	1,048	883,386	2,641,884
% All PV Occupant Crashes	30.2%	4.0%	32.4%	36.8%
Lane Departure Crashes	1,126,397	9,428	479,939	863,213
% All PV Occupant Crashes	20.0%	35.8%	17.6%	12.0%
Blind Spot Crashes	503,070	542	188,304	860,726
% All PV Occupant Crashes	8.9%	2.1%	6.9%	12.0%
Pedestrian Crashes	111641	4106	104066	6985
% All PV Participant Crashes	2.0%	15.6%	3.8%	0.1%
Total, All Tech Groups	3,333,008	11,017	1,551,629	4,365,823
Total, % All PV Occupant Crashes	61.1%	57.5%	60.7%	64.2%
All Crashes	5,640,000	26,364	2,730,000	7,170,000

7.2.5. Fleet Penetration Schedules

The third element of the rule's safety projections is the fleet technology penetration schedules. ADAS will only influence the safety of future model year fleets to the extent that they are installed and used in those fleets. These technologies are already being installed on some vehicles to varying degrees, but the agency expects that over time, they will become standard equipment due to some combination of market pressure and/or safety regulation. NHTSA adopts this assumption based on the history of most previous vehicle safety technologies, which are now standard equipment on all new vehicles sold in the United States.

The pace of technology adoption is estimated based on a variety of factors, but the most fundamental is the current pace of adoption in recent years. These published data were obtained from Ward's Automotive Reports for each technology.[1107] Since these technologies are relatively recent, only a few years of data—typically 2 or 3 years—were available from which to derive a trend. This makes these projections uncertain, but under these circumstances, a continuation of the known trend is the baseline assumption, which we modify only when there is a rationale to justify it.

The technologies are examined in pairs reflecting their mutual target populations. Both FCW and AEB affect the same target population—frontal collisions. Both systems have been installed in some current model year vehicles, but their relative paces are expected to diverge significantly due to a formal agreement brokered by NHTSA and IIHS involving nearly all auto manufacturers, to have AEB installed in 100 percent of their vehicles by September 2022 (model year 2023).[1108] Ward's first published installation rates for FCW and AEB for the 2016 model year and as of this analysis the 2021 model year is the latest data they have published. We thus have data indicating that FCW was installed in 17.6 percent of model year 2016 vehicles

[1107] Derived from Ward's Automotive Yearbooks, 2014 through 2021, % Factory Installed Electronic ADAS Equipment tables, weighting domestic and imported passenger cars and LTs by sales volume.
[1108] NHTSA. 2017. NHTSA-IIHS Announcement on AEB. Last revised: Dec. 21, 2017. Available at: https://www.nhtsa.gov/press-releases/nhtsa-iihs-announcement-aeb. (Accessed: May 31, 2023).

and 81.6 percent of model year 2021 vehicles. By 2021, all vehicles with FCW also incorporated AEB. AEB was installed in 12.0 percent of model year 2016 vehicles and 81.6 percent of model year 2021 vehicles. More recent reports submitted by manufacturers to the Federal Register indicate that installation rates accelerated in model year 2018 and 2019 vehicles. Four manufacturers, Tesla, Volvo, Audi, and Mercedes have already met their voluntary commitment of 100 percent installation 3 years ahead of schedule. During the period, September 1, 2019, through August 31, 2020, 14 of the 20 manufacturers equipped more than 75 percent of their new PVs with AEB, and overall manufacturers equipped more than 13.5 million new PVs with AEB.[1109]

Because of the NHTSA/IIHS agreement, NHTSA assumed that some form of AEB will be in 100 percent of light vehicles by model year 2023. To derive installation rates for model years 2021 through 2022, NHTSA interpolated between the model year 2021 rate of 81.6 percent and the model year 2023 rate of 100 percent. To derive a model year 2015 estimate, NHTSA modelled the results for model years 2016-2023 and calculated a value for year x=0, essentially extending the model results back one year on the same trendline.

For FCW, NHTSA used the same interpolation/modeling method as was used for AEB to derive an initial baseline trend. However, while both systems are available on a portion of the current model year fleet, the agency anticipates that by model year 2023, all vehicles will have AEB systems that essentially encompass both FCW and AEB functions. NHTSA therefore projects a gradual increase in both systems until the sum of both systems penetration rates exceeds 100 percent. At that point, the agency projects a gradual decrease in FCW only installations until FCW only systems are completely replaced by AEB systems in model year 2023.

For LDW, Ward's penetration data were available as far back as model year 2013, giving a total of 9 data points through model year 2021. The projection for LDW was derived by modelling these data points. The data indicate a near linear trend and our initial projections of future years were derived directly from this model. Ward's did not report any of the more advanced LKA systems until model year 2016, leaving only 6 data points through 2021. NHTSA modelled a simple trendline through these data points to estimate the pace of future LKA installations. As with Frontal crashes, the agency assumes a gradual phase-in of the most effective technology, LKA, will eventually replace the lesser technology, LDW, and NHTSA allows gradual increases in both systems penetration until their sum exceeds 100 percent, at which point LDW penetration begins to decline to zero while LKA penetration climbs to 100 percent.

For blind spot crashes, Ward's data were available for model years 2013-2021 for BSD. We used Reverse Collision Detection (RCD) in Ward's as a proxy for LCA installations since the sensors used in RCD are the same as those necessary for LCA to function. LCA systems were available as optional equipment on at least 10 model year 2016 vehicles.[1110] BSD is calculated as the difference between Blind Spot Alert (BSA) reported in Ward's and RCD, since BSA includes both BSD and LCA systems. From this we are able to measure the installation rates of BSD and LCA systems from model year 2016 to model year 2021. As with frontal and lane change technologies, the agency assumes a gradual phase-in of the most effective technology, LCA, will eventually replace the lesser technology, BSD, and the agency allows gradual increases in both systems penetration until their sum exceeds 100 percent, at which point BSD penetration begins to decline to zero while LCA penetration climbs to 100 percent.

Installation rates for PAEB were extracted from Ward's tables for model years 2016-2021. PAEB was introduced in 2015 and was set to 0 initially in the table. A linear extrapolation of the data suggests that installation of PAEB will be 100% by MY2024. Values from model year 2022 and 2023 were extrapolated from a linear forecast.

7.2.6. Impact Calculations

Table 7-12, Table 7-13, Table 7-14, and Table 7-15, summarize the resulting estimates of impacts on fatality rates for frontal crash technologies, lane change technologies, blind spot technologies, and pedestrian

[1109] NHTSA. 2020. NHTSA Announces Update to Historic AEB Commitment by 20 Automakers. Dec. 17, 2020. Available at: https://www.nhtsa.gov/press-releases/nhtsa-announces-2020-update-aeb-installation-20-automakers. (Accessed: May 31, 2023).
[1110] Threewitt, C. 2023. 10 Cars with Lane Assist Using Cameras or Sensors. Available at: https://www.autobytel.com/car-buying-guides/features/10-cars-with-lane-change-assist-using-cameras-or-sensors-130847. (Accessed: Feb. 16, 2024).

collision mitigation technologies for model years 2015-2035. All previously discussed inputs are shown in the tables. The effect of each technology is the product of its effectiveness, the percent installation in the model year fleet, and the portion of the total light vehicle occupant target population that each technology might address. Since installation rates for each technology apply to different portions of the vehicle fleet (i.e., vehicles have either the more basic or more advanced version of the technology), the effect of the two technologies combined is a simple sum of the two effects. Similarly, because each crash type addresses a unique target population, there is no overlap among the three crash types and the sum of the normalized crash impacts across all three crash types represents the total impact on fatality rates from these 6 technologies for each model year. These cumulative results are shown in the last column of Table 7-15. As technologies phase in to newer model year fleets,[1111] their impact on the light vehicle occupant fatality rate increases proportionally to roughly 8.5 percent before levelling off. That is, eventually, by approximately model year 2026, these technologies are ultimately expected to reduce fatalities and fatality rates for new vehicles by 8.6 percent from their initial baseline levels.

Table 7-12: Phased Impact of Crashworthiness Technologies on Fatality Rates, Forward Collision Crashes

MY	Forward Collision Warning		Automatic Emergency Braking		% T.P.	Weighted Effectiveness
	FCW Eff.	% Inst.	AEB Eff.	% Inst.		
2015	10.5%	0.047	23.0%	0.011	4.0%	0.00029
2016	10.5%	0.056	23.0%	0.120	4.0%	0.00133
2017	10.5%	0.035	23.0%	0.270	4.0%	0.00261
2018	10.5%	0.021	23.0%	0.445	4.0%	0.00416
2019	10.5%	0.018	23.0%	0.583	4.0%	0.00540
2020	10.5%	0.006	23.0%	0.741	4.0%	0.00600
2021	10.5%	0.001	23.0%	0.816	4.0%	0.00746
2022	10.5%	0.000	23.0%	0.940	4.0%	0.00859
2023	10.5%	0.000	23.0%	1	4.0%	0.00914
2024	10.5%	0.000	23.0%	1	4.0%	0.00914
2025	10.5%	0.000	23.0%	1	4.0%	0.00914
2026	10.5%	0.000	23.0%	1	4.0%	0.00914
2027	10.5%	0.000	23.0%	1	4.0%	0.00914
2028	10.5%	0.000	23.0%	1	4.0%	0.00914
2029	10.5%	0.000	23.0%	1	4.0%	0.00914
2030	10.5%	0.000	23.0%	1	4.0%	0.00914
2031	10.5%	0.000	23.0%	1	4.0%	0.00914
2032	10.5%	0.000	23.0%	1	4.0%	0.00914
2033	10.5%	0.000	23.0%	1	4.0%	0.00914
2034	10.5%	0.000	23.0%	1	4.0%	0.00914
2035	10.5%	0.000	23.0%	1	4.0%	0.00914

[1111] While it is technically possible to retrofit these systems into the on-road fleet, such retrofits would be significantly more expensive than OEM installations. NHTSA thus assumes all on-road fleet penetration of these technologies will come through new vehicle sales.

Table 7-13: Phased Impact of Crashworthiness Technologies on Fatality Rates, Lane Departure Crashes

MY	Lane Departure Warning		Lane Keep Assist		% T.P.	Weighted Effectiveness
	LDW Eff.	% Inst.	LKA Eff.	% Inst.		
2015	10.0%	0.177	20.0%	0.000	35.8%	0.00632
2016	10.0%	0.110	20.0%	0.088	35.8%	0.010221
2017	10.0%	0.075	20.0%	0.205	35.8%	0.017367
2018	10.0%	0.084	20.0%	0.324	35.8%	0.026198
2019	10.0%	0.037	20.0%	0.442	35.8%	0.03294
2020	10.0%	0.092	20.0%	0.586	35.8%	0.045219
2021	10.0%	0.110	20.0%	0.650	35.8%	0.050438
2022	10.0%	0.100	20.0%	0.743	35.8%	0.056741
2023	10.0%	0.091	20.0%	0.836	35.8%	0.063044
2024	10.0%	0.071	20.0%	0.929	35.8%	0.068983
2025	10.0%	0.000	20.0%	1.000	35.8%	0.071519
2026	10.0%	0	20.0%	1	35.8%	0.071519
2027	10.0%	0	20.0%	1	35.8%	0.071519
2028	10.0%	0	20.0%	1	35.8%	0.071519
2029	10.0%	0	20.0%	1	35.8%	0.071519
2030	10.0%	0	20.0%	1	35.8%	0.071519
2031	10.0%	0	20.0%	1	35.8%	0.071519
2032	10.0%	0	20.0%	1	35.8%	0.071519
2033	10.0%	0	20.0%	1	35.8%	0.071519
2034	10.0%	0	20.0%	1	35.8%	0.071519
2035	10.0%	0	20.0%	1	35.8%	0.071519

Table 7-14: Phased Impact of Crashworthiness Technologies on Fatality Rates, Blind Spot Crashes and Combined Total – All Three Crash Types

MY	Blind Spot Detection		Lane Change Assist		% T.P.	Weighted Effectiveness
	BSD Eff.	% Inst.	LCA Eff.	% Inst.		
2015	3.0%	0.206	26.0%	0.000	2.1%	0.00013
2016	3.0%	0.311	26.0%	0.000	2.1%	0.00019
2017	3.0%	0.389	26.0%	0.000	2.1%	0.00024
2018	3.0%	0.398	26.0%	0.051	2.1%	0.00052
2019	3.0%	0.459	26.0%	0.095	2.1%	0.00079
2020	3.0%	0.446	26.0%	0.163	2.1%	0.00115
2021	3.0%	0.469	26.0%	0.241	2.1%	0.00158
2022	3.0%	0.492	26.0%	0.289	2.1%	0.00185
2023	3.0%	0.516	26.0%	0.337	2.1%	0.00212
2024	3.0%	0.540	26.0%	0.385	2.1%	0.00239

2025	3.0%	0.564	26.0%	0.433	2.1%	0.00266
2026	3.0%	0.519	26.0%	0.481	2.1%	0.00289
2027	3.0%	0.471	26.0%	0.529	2.1%	0.00312
2028	3.0%	0.422	26.0%	0.578	2.1%	0.00335
2029	3.0%	0.374	26.0%	0.626	2.1%	0.00358
2030	3.0%	0.326	26.0%	0.674	2.1%	0.00380
2031	3.0%	0.278	26.0%	0.722	2.1%	0.00403
2032	3.0%	0.230	26.0%	0.770	2.1%	0.00426
2033	3.0%	0.182	26.0%	0.818	2.1%	0.00447
2034	3.0%	0.134	26.0%	0.866	2.1%	0.00471
2035	3.0%	0.085	26.0%	0.915	2.1%	0.00494

Table 7-15: Phased Impact of Crashworthiness Technologies on Fatality Rates, Pedestrian Crashes and Combined Total – All Four Crash Types

MY	Pedestrian Automatic Emergency Braking		% T.P.	Weighted Effectiveness	Four Techs Avg. Effectiveness
	PAEB Eff.	% Inst.			
2015	17.1%	0.000	15.6%	0.000000	0.006739
2016	17.1%	0.074	15.6%	0.001974	0.013719
2017	17.1%	0.179	15.6%	0.004791	0.025011
2018	17.1%	0.310	15.6%	0.008262	0.039133
2019	17.1%	0.458	15.6%	0.012224	0.051358
2020	17.1%	0.638	15.6%	0.017031	0.070195
2021	17.1%	0.746	15.6%	0.019922	0.079398
2022	17.1%	0.840	15.6%	0.022412	0.089589
2023	17.1%	0.933	15.6%	0.024903	0.099204
2024	17.1%	1.000	15.6%	0.026694	0.107207
2025	17.1%	1.000	15.6%	0.026694	0.110015
2026	17.1%	1.000	15.6%	0.026694	0.110244
2027	17.1%	1.000	15.6%	0.026694	0.110472
2028	17.1%	1.000	15.6%	0.026694	0.110699
2029	17.1%	1.000	15.6%	0.026694	0.110927
2030	17.1%	1.000	15.6%	0.026694	0.111155
2031	17.1%	1.000	15.6%	0.026694	0.111382
2032	17.1%	1.000	15.6%	0.026694	0.111610
2033	17.1%	1.000	15.6%	0.026694	0.111837
2034	17.1%	1.000	15.6%	0.026694	0.112065
2035	17.1%	1.000	15.6%	0.026694	0.112293

The inputs and weighted effectiveness for nonfatal injuries are summarized in Table 7-16 through Table 7-19 and for PDOs in Table 7-20 through Table 7-23.[1112]

Table 7-16: Phased Impact of Crashworthiness Technologies on Non-Fatal Injury Rates, Forward Collision Crashes

MY	Forward Collision Warning		Automatic Emergency Braking			Weighted Effectiveness
	Eff.	% Inst.	Eff.	% Inst.	% T.P.	
2015	21.0%	0.047	46.0%	0.011	32.4%	0.004757
2016	21.0%	0.06	46.0%	0.120	32.4%	0.021707
2017	21.0%	0.04	46.0%	0.270	32.4%	0.042556
2018	21.0%	0.02	46.0%	0.445	32.4%	0.067718
2019	21.0%	0.02	46.0%	0.583	32.4%	0.087989
2020	21.0%	0.01	46.0%	0.741	32.4%	0.110722
2021	21.0%	0.00	46.0%	0.816	32.4%	0.121550
2022	21.0%	0.00	46.0%	0.940	32.4%	0.139880
2023	21.0%	0	46.0%	1	32.4%	0.148849
2024	21.0%	0	46.0%	1	32.4%	0.148849
2025	21.0%	0	46.0%	1	32.4%	0.148849
2026	21.0%	0	46.0%	1	32.4%	0.148849
2027	21.0%	0	46.0%	1	32.4%	0.148849
2028	21.0%	0	46.0%	1	32.4%	0.148849
2029	21.0%	0	46.0%	1	32.4%	0.148849
2030	21.0%	0	46.0%	1	32.4%	0.148849
2031	21.0%	0	46.0%	1	32.4%	0.148849
2032	21.0%	0	46.0%	1	32.4%	0.148849
2033	21.0%	0	46.0%	1	32.4%	0.148849
2034	21.0%	0	46.0%	1	32.4%	0.148849
2035	21.0%	0	46.0%	1	32.4%	0.148849

Table 7-17: Phased Impact of Crashworthiness Technologies on Non-Fatal Injury Rates, Lane Departure Crashes

MY	Lane Departure Warning		Lane Keep Assist		% T.P.	Weighted Effectiveness
	Eff.	% Inst.	Eff.	% Inst.		
2015	10.0%	0.177	20.0%	0.000	17.6%	0.003107
2016	10.0%	0.110	20.0%	0.088	17.6%	0.005025
2017	10.0%	0.075	20.0%	0.205	17.6%	0.008538
2018	10.0%	0.084	20.0%	0.324	17.6%	0.012879
2019	10.0%	0.037	20.0%	0.442	17.6%	0.016194

[1112] See previous discussion in this subchapter for the studies and methodology used to create these estimates.

2020	10.0%	0.092	20.0%	0.586	17.6%	0.022231
2021	10.0%	0.110	20.0%	0.650	17.6%	0.024797
2022	10.0%	0.100	20.0%	0.743	17.6%	0.027895
2023	10.0%	0.091	20.0%	0.836	17.6%	0.030994
2024	10.0%	0.071	20.0%	0.929	17.6%	0.033914
2025	10.0%	0.000	20.0%	1.000	17.6%	0.035160
2026	10.0%	0	20.0%	1	17.6%	0.035160
2027	10.0%	0	20.0%	1	17.6%	0.035160
2028	10.0%	0	20.0%	1	17.6%	0.035160
2029	10.0%	0	20.0%	1	17.6%	0.035160
2030	10.0%	0	20.0%	1	17.6%	0.035160
2031	10.0%	0	20.0%	1	17.6%	0.035160
2032	10.0%	0	20.0%	1	17.6%	0.035160
2033	10.0%	0	20.0%	1	17.6%	0.035160
2034	10.0%	0	20.0%	1	17.6%	0.035160
2035	10.0%	0	20.0%	1	17.6%	0.035160

Table 7-18: Phased Impact of Crashworthiness Technologies on Non-Fatal Injury Rates, Blind Spot Crashes and Combined Total – All Three Crash Types, and Final Multiplier

MY	Blind Spot Detection		Lane Change Assist		% T.P.	Weighted Effectiveness
	Eff.	% Inst.	Eff.	% Inst.		
2015	3.0%	0.206	26.0%	0.000	6.9%	0.000426
2016	3.0%	0.311	26.0%	0.000	6.9%	0.000643
2017	3.0%	0.389	26.0%	0.000	6.9%	0.000804
2018	3.0%	0.398	26.0%	0.051	6.9%	0.001730
2019	3.0%	0.459	26.0%	0.095	6.9%	0.002657
2020	3.0%	0.446	26.0%	0.163	6.9%	0.003848
2021	3.0%	0.469	26.0%	0.241	6.9%	0.005286
2022	3.0%	0.492	26.0%	0.289	6.9%	0.006198
2023	3.0%	0.516	26.0%	0.337	6.9%	0.007111
2024	3.0%	0.540	26.0%	0.385	6.9%	0.008023
2025	3.0%	0.564	26.0%	0.433	6.9%	0.008936
2026	3.0%	0.519	26.0%	0.481	6.9%	0.009706
2028	3.0%	0.422	26.0%	0.578	6.9%	0.011233
2029	3.0%	0.374	26.0%	0.626	6.9%	0.011997
2030	3.0%	0.326	26.0%	0.674	6.9%	0.012760
2031	3.0%	0.278	26.0%	0.722	6.9%	0.013524
2032	3.0%	0.230	26.0%	0.770	6.9%	0.014288

2033	3.0%	0.182	26.0%	0.818	6.9%	0.015051
2034	3.0%	0.134	26.0%	0.866	6.9%	0.015815
2035	3.0%	0.085	26.0%	0.915	6.9%	0.016577

Table 7-19: Phased Impact of Crashworthiness Technologies on Non-Fatal Injury Rates, Pedestrian AEB, Pedestrian Crashes, and Final Multiplier

MY	PAEBS				Seven Techs Average Eff. Impact	Multiplier/ Fatalities
	Eff.	% Inst.	% T.P.	Weighted Effectiveness		
2015	25.0%	0.000	3.8%	0.000000	0.008289	1.230119
2016	25.0%	0.074	3.8%	0.000705	0.028079	2.046706
2017	25.0%	0.179	3.8%	0.001710	0.053609	2.143425
2018	25.0%	0.310	3.8%	0.002950	0.085277	2.179139
2019	25.0%	0.458	3.8%	0.004364	0.111204	2.165264
2020	25.0%	0.638	3.8%	0.006080	0.142881	2.035498
2021	25.0%	0.746	3.8%	0.007112	0.158745	1.999347
2022	25.0%	0.840	3.8%	0.008001	0.181975	2.031228
2023	25.0%	0.933	3.8%	0.008890	0.195844	1.974147
2024	25.0%	1.000	3.8%	0.009530	0.200316	1.868499
2025	25.0%	1.000	3.8%	0.009530	0.202475	1.840434
2026	25.0%	1.000	3.8%	0.009530	0.203245	1.843588
2027	25.0%	1.000	3.8%	0.009530	0.204009	1.846702
2028	25.0%	1.000	3.8%	0.009530	0.204772	1.849804
2029	25.0%	1.000	3.8%	0.009530	0.205536	1.852892
2030	25.0%	1.000	3.8%	0.009530	0.206300	1.855969
2031	25.0%	1.000	3.8%	0.009530	0.207063	1.859032
2032	25.0%	1.000	3.8%	0.009530	0.207827	1.862083
2033	25.0%	1.000	3.8%	0.009530	0.208590	1.865122
2034	25.0%	1.000	3.8%	0.009530	0.209354	1.868148
2035	25.0%	1.000	3.8%	0.009530	0.210118	1.871162

Table 7-20: Phased Impact of Crashworthiness Technologies on PDO Crash Rates, Forward Collision Crashes

MY	Forward Collision Warning		Automatic Emergency Braking			Weighted Effectiveness
	FCW Eff.	% Inst.	AEB Eff.	% Inst.	% T.P.	
2015	21.0%	0.047	46.0%	0.011	36.8%	0.005416
2016	21.0%	0.06	46.0%	0.120	36.8%	0.024717
2017	21.0%	0.04	46.0%	0.270	36.8%	0.048458
2018	21.0%	0.02	46.0%	0.445	36.8%	0.077110

2019	21.0%	0.02	46.0%	0.583	36.8%	0.100192
2020	21.0%	0.01	46.0%	0.741	36.8%	0.126078
2021	21.0%	0.00	46.0%	0.816	36.8%	0.138408
2022	21.0%	0.00	46.0%	0.940	36.8%	0.159280
2023	21.0%	0	46.0%	1	36.8%	0.169493
2024	21.0%	0	46.0%	1	36.8%	0.169493
2025	21.0%	0	46.0%	1	36.8%	0.169493
2026	21.0%	0	46.0%	1	36.8%	0.169493
2027	21.0%	0	46.0%	1	36.8%	0.169493
2028	21.0%	0	46.0%	1	36.8%	0.169493
2029	21.0%	0	46.0%	1	36.8%	0.169493
2030	21.0%	0	46.0%	1	36.8%	0.169493
2031	21.0%	0	46.0%	1	36.8%	0.169493
2032	21.0%	0	46.0%	1	36.8%	0.169493
2033	21.0%	0	46.0%	1	36.8%	0.169493
2034	21.0%	0	46.0%	1	36.8%	0.169493
2035	21.0%	0	46.0%	1	36.8%	0.169493

Table 7-21: Phased Impact of Crashworthiness Technologies on PDO Crash Rates, Lane Departure Crashes

MY	Lane Departure Warning		Lane Keep Assist		% T.P.	Weighted Effectiveness
	LDW Eff.	% Inst.	LKA Eff.	% Inst.		
2015	10.0%	0.177	20.0%	0.000	12.0%	0.002128
2016	10.0%	0.110	20.0%	0.088	12.0%	0.003441
2017	10.0%	0.075	20.0%	0.205	12.0%	0.005847
2018	10.0%	0.084	20.0%	0.324	12.0%	0.008820
2019	10.0%	0.037	20.0%	0.442	12.0%	0.011090
2020	10.0%	0.092	20.0%	0.586	12.0%	0.015224
2021	10.0%	0.110	20.0%	0.650	12.0%	0.016981
2022	10.0%	0.100	20.0%	0.743	12.0%	0.019103
2023	10.0%	0.091	20.0%	0.836	12.0%	0.021225
2024	10.0%	0.071	20.0%	0.929	12.0%	0.023225
2025	10.0%	0.000	20.0%	1.000	12.0%	0.024078
2026	10.0%	0	20.0%	1	12.0%	0.024078
2027	10.0%	0	20.0%	1	12.0%	0.024078
2028	10.0%	0	20.0%	1	12.0%	0.024078
2029	10.0%	0	20.0%	1	12.0%	0.024078
2030	10.0%	0	20.0%	1	12.0%	0.024078

2031	10.0%	0	20.0%	1	12.0%	0.024078
2032	10.0%	0	20.0%	1	12.0%	0.024078
2033	10.0%	0	20.0%	1	12.0%	0.024078
2034	10.0%	0	20.0%	1	12.0%	0.024078
2035	10.0%	0	20.0%	1	12.0%	0.024078

Table 7-22: Phased Impact of Crashworthiness Technologies on PDO Crash Rates, Blind Spot Crashes and Combined Total – All Three Crash Types

MY	Blind Spot Detection		Lane Change Assist		% T.P.	Weighted Effectiveness
	Eff.	% Inst.	Eff.	% Inst.		
2015	3.0%	0.206	26.0%	0.000	12.0%	0.000741
2016	3.0%	0.311	26.0%	0.000	12.0%	0.001118
2017	3.0%	0.389	26.0%	0.000	12.0%	0.001399
2018	3.0%	0.398	26.0%	0.051	12.0%	0.003010
2019	3.0%	0.459	26.0%	0.095	12.0%	0.004625
2020	3.0%	0.446	26.0%	0.163	12.0%	0.006697
2021	3.0%	0.469	26.0%	0.241	12.0%	0.009199
2022	3.0%	0.492	26.0%	0.289	12.0%	0.010787
2023	3.0%	0.516	26.0%	0.337	12.0%	0.012375
2024	3.0%	0.540	26.0%	0.385	12.0%	0.013964
2025	3.0%	0.564	26.0%	0.433	12.0%	0.015552
2026	3.0%	0.519	26.0%	0.481	12.0%	0.016892
2027	3.0%	0.471	26.0%	0.529	12.0%	0.018221
2028	3.0%	0.422	26.0%	0.578	12.0%	0.019550
2029	3.0%	0.374	26.0%	0.626	12.0%	0.020879
2030	3.0%	0.326	26.0%	0.674	12.0%	0.022208
2031	3.0%	0.278	26.0%	0.722	12.0%	0.023537
2032	3.0%	0.230	26.0%	0.770	12.0%	0.024866
2033	3.0%	0.182	26.0%	0.818	12.0%	0.026195
2034	3.0%	0.134	26.0%	0.866	12.0%	0.027524
2035	3.0%	0.085	26.0%	0.915	12.0%	0.028853

Table 7-23: Phased Impact of Crashworthiness Technologies on PDO Crash Rates, Pedestrian AEB, Pedestrian Crashes, and Final Multiplier

MY	PAEBS				Four Techs Average Eff. Impact	Multiplier/ Fatalities
	Eff.	% Inst.	% T.P.	Weighted Effectiveness		

2015	0.1%	0.000	0.1%	0.000000	0.008285	1.229481
2016	0.1%	0.074	0.1%	0.000000	0.029277	2.134028
2017	0.1%	0.179	0.1%	0.000000	0.055705	2.227235
2018	0.1%	0.310	0.1%	0.000000	0.088941	2.272765
2019	0.1%	0.458	0.1%	0.000000	0.115907	2.256840
2020	0.1%	0.638	0.1%	0.000001	0.148000	2.108427
2021	0.1%	0.746	0.1%	0.000001	0.164590	2.072960
2022	0.1%	0.840	0.1%	0.000001	0.189172	2.111562
2023	0.1%	0.933	0.1%	0.000001	0.203095	2.047239
2024	0.1%	1.000	0.1%	0.000001	0.206682	1.927887
2025	0.1%	1.000	0.1%	0.000001	0.209124	1.900876
2026	0.1%	1.000	0.1%	0.000001	0.210465	1.909076
2027	0.1%	1.000	0.1%	0.000001	0.211794	1.917174
2028	0.1%	1.000	0.1%	0.000001	0.213123	1.925238
2029	0.1%	1.000	0.1%	0.000001	0.214452	1.933269
2030	0.1%	1.000	0.1%	0.000001	0.215781	1.941267
2031	0.1%	1.000	0.1%	0.000001	0.217110	1.949232
2032	0.1%	1.000	0.1%	0.000001	0.218439	1.957165
2033	0.1%	1.000	0.1%	0.000001	0.219768	1.965066
2034	0.1%	1.000	0.1%	0.000001	0.221097	1.972935
2035	0.1%	1.000	0.1%	0.000001	0.222426	1.980771

Based on a comparison of the combined average effectiveness impacts for the three crash severity groups (fatalities, non-fatal injuries, and property damage), it is apparent that these advanced crash avoidance technologies will reduce non-fatal injuries and property damage crashes by more than they would fatalities[1113]

7.2.7. Impact of Advanced Technologies on Older Vehicles' Fatality Rates

The users of older vehicles will also benefit from crash avoidance technologies on newer vehicles when those technologies prevent multi-vehicle crashes with older vehicles. Crash avoidance technologies prevent crashes from happening and thus benefit both the vehicle with the technology and any other vehicles that it might have collided with. However, the scope of these impacts on older vehicle's fatality rates are somewhat limited due to several factors:

1. Single vehicle crashes, which make up about half of all fatal crashes, will not be affected. Only multi-vehicle crashes involving a newer vehicle with the advanced technology and an older vehicle will be affected. Multi-vehicle crashes account for roughly half of all light vehicle occupant fatalities.
2. For a new safety technology to benefit an older vehicle in a multi-vehicle crash, the vehicle with the technology must have been able to control or prevent the crash. For example, in front-to-rear crashes which can be addressed by FCW and AEB, the older vehicle would only benefit if it was the vehicle struck from behind. If the struck vehicle were the newer vehicle, its AEB technology would not prevent the crash. Logically this would occur in roughly half of two-vehicle crashes and a third of all three- vehicle crashes.

[1113] For example, for model year 2035, the combined effectiveness for PDO crashes is .224784, as shown in the second to last column of Table 7-28, which is 2.613 times the .0860 combined effectiveness for fatalities, as seen in Table 7-13, which shows the disproportionality impact of crash avoidance technologies on non-fatal accidents.

Since most multi-vehicle crashes involve only two vehicles, roughly half of all multi-vehicle crashes might qualify.

3. The benefits experienced by older vehicles are proportional to the probability that the vehicles they collide with are newer vehicles with advanced crash avoidance technology. We estimate that the probability that this would occur is a function of the relative exposure of vehicles by age, measured by the portion of total VMT driven by vehicles of that age. Based on VMT schedules (see calendar year 2016 example in Table 7-24) new (current model year) vehicles account for about 9.6 percent of annual fleet VMT. The relevant portion would increase over time as additional model year vehicles are produced with advanced technologies. However, the portion of older vehicle crashes that might be affected by newer technologies is initially very small—only about 2 percent (0.5*0.5*0.096) of older vehicles involved in crashes might benefit from advanced crash avoidance technologies in other vehicles in the first year.

Table 7-24: Registrations, Total VMT, and Proportions of Total VMT by Vehicle Age

Registrations, Total VMT, And Proportions of Total VMT By Vehicle Age				
Model Year	Age	CY 2016 Registrations	VMT (thousand)	% Total VMT
1977	39	286,019	927,877	0.000329
1978	38	332,760	1,247,190	0.000443
1979	37	375,561	1,556,553	0.000553
1980	36	205,942	903,948	0.000321
1981	35	208,192	1,010,499	0.000359
1982	34	213,697	1,130,039	0.000401
1983	33	265,583	1,496,439	0.000531
1984	32	408,058	2,428,835	0.000862
1985	31	477,178	2,993,451	0.001063
1986	30	605,932	3,991,280	0.001417
1987	29	644,568	4,396,414	0.001561
1988	28	629,179	4,431,880	0.001574
1989	27	747,740	5,475,868	0.001944
1990	26	755,244	5,685,511	0.002019
1991	25	899,252	6,991,287	0.002483
1992	24	1,005,716	8,055,442	0.00286
1993	23	1,308,396	10,784,619	0.003829

Table 7-24 (continued): Registrations, Total VMT, and Proportions of Total VMT by Vehicle Age

Registrations, Total VMT, And Proportions of Total VMT By Vehicle Age				
Model Year	Age	CY 2016 Registrations	VMT (thousand)	% Total VMT
1994	22	1,738,409	14,739,099	0.005234
1995	21	2,212,145	19,191,169	0.006815
1996	20	2,364,368	21,059,984	0.007478
1997	19	3,401,992	31,134,256	0.011055
1998	18	4,079,728	38,358,375	0.013621

1999	17	5,377,629	52,039,074	0.018478
2000	16	6,826,267	67,907,099	0.024113
2001	15	7,475,530	76,512,692	0.027169
2002	14	8,912,404	94,016,400	0.033384
2003	13	9,825,521	106,764,943	0.037911
2004	12	10,806,847	121,080,704	0.042994
2005	11	11,649,021	134,404,144	0.047725
2006	10	11,699,430	138,962,811	0.049344
2007	9	12,519,932	153,300,527	0.054435
2008	8	11,781,605	148,871,424	0.052862
2009	7	8,171,782	106,120,610	0.037682
2010	6	9,944,848	133,696,015	0.047474
2011	5	10,967,994	152,795,831	0.054256
2012	4	12,409,627	177,760,326	0.06312
2013	3	14,197,792	210,386,962	0.074706
2014	2	14,726,690	226,423,858	0.0804
2015	1	16,208,153	257,415,893	0.091405
2016	0	16,338,755	269,760,666	0.095789
Total		223,005,486	2,816,209,994	1

To reflect this safety benefit for older vehicles, NHTSA calculated a revised fatality rate for each older model year vehicle on the road based on its interaction with each new model year starting with model year 2021 vehicles based on the following relationship:

$$\text{Revised Fatality Rate} = Fm\big((x-y)mnp\big) + F(1-m)$$

Where:

F = initial fatality rate for each model year

x = baseline model year fatality rate

y = current model year fatality rate

m = proportion of occupant fatalities that occur in the multi-vehicle crashes (52 percent)

n = probability that crash is with a new model year vehicle containing advanced safety technologies

p = probability that a new vehicle is “striking” vehicle

The initial fatality rate for each vehicle model year (F) was derived by combining fatality counts from NHTSA’s FARS with VMT data from IHS/Polk.

The baseline model year fatality rate (x) represents the baseline rate over which the impact of new crash avoidance technologies should be measured. It establishes the baseline rate for each model year that will be compared to the most current model year rate to determine the change in fatality rate (FR) for each model year. The relative effectiveness of new crash-avoidance technologies in modifying the fatality rate of older model vehicles is measured differently depending on the age of the older vehicle. The fatality rate is a historical measure that reflects safety differences due to both crashworthiness technologies such as air bags and crash avoidance technologies such as electronic stability control, but up through model year 2017, crashworthiness standards are the predominate cause of these differences.

The most recent significant crashworthiness safety standard, which upgraded roof strength standards, was effective in all new PVs in model year 2017. Crashworthiness standards would not have secondary benefits for older model year vehicles. Post model year 2017, NHTSA believes crash avoidance technologies will drive safety improvements. To isolate the added crash avoidance safety expected in newer vehicles, the marginal impact of the difference between the model year 2017 fatality rate and the most current model year fatality rate represents the added marginal effectiveness of new crash-avoidance technologies of each subsequent model year for model years 2017 and earlier. Beginning with model year 2018, the difference between the older model year fatality rate and most current model year rate determines the potential safety benefit for the older vehicles.

The current model year fatality rate (y) represents the projected fatality rate of future model year vehicles after adjustment for the impacts of the advanced crash avoidance technologies and projected improvements in non-technology factors examined in this analysis. This process was discussed in detail in the previous subchapter.

The proportion of PV occupant fatalities that occur in multi-vehicle crashes (m), was derived from an analysis of occupants of fatal PV crashes from 2002-2017 FARS. The analysis indicated that 47.8 percent of fatal crash occupants were in single vehicle crashes, 40.2 percent were in two vehicle crashes, and 12 percent were in crashes involving 3 or more vehicles. Overall, 52.2 percent were in multi-vehicle crashes.

The portion of older vehicle crashes involving newer vehicles containing advanced crash avoidance technologies (n), is assumed to be equal to the cumulative risk exposure of vehicles that have these technologies. This exposure is measured by the product of annual VMT by vehicle age and registrations of vehicles of that age. The CAFE Model calculates this dynamically, but as an example, based on 2016 registration data (see Table 7-24), the most current model year would represent 9.6 percent of all VMT in a calendar year, implying a 9.6 percent probability that the vehicle encountered would be from the most current model year. This percentage would increase for each calendar year as more model year vehicles adopt advanced crashworthiness technologies. NHTSA notes that other factors such as uneven concentrations of newer vs. older vehicles or improved crash avoidance in the younger vehicles already on the road that are the basis for our VMT proportion table might disrupt this assumption, but it is likely that this would only serve to slow the probability of these encounters, making this a conservative assumption in that it maximizes the probability that older vehicles might benefit from newer technologies.

The probability that the vehicle with advanced crash avoidance technology is the controlling or striking vehicle (p), was calculated using the relative frequency of fatal crash occupants in multi-vehicle crashes. As noted previously, 40.2 percent were in two vehicle crashes, and 12 percent were in crashes involving 3 or more vehicles. NHTSA assumes a probability of 50 percent for two vehicle crashes and 33 percent for crashes with 3 or more vehicles. Weighted together we estimate a 46.1 percent probability that, given a multi-vehicle crash involving a vehicle with advanced technologies and an older vehicle without them, the newer vehicle will be the striking vehicle or in a position where its crash avoidance technologies might influence the outcome of the crash with the older vehicle.

This process is illustrated in Table 7-25 below for adjustments due to improvements in model year 2021 vehicles back through model year 1995. In Table 7-25 the actual model year fatality rate is shown in the second column. As noted above, the base fatality rate, shown in column 3, is the model year 2017 rate for all model years prior to 2018, after which it becomes the actual model year rate. Column 4 shows the difference between the fatality rate for model year 2021 and the base rate for each model year. Column 5 shows the resulting revised fatality rate that would be used for each older model year, and columns 6 and 7 list the change in that rate. The various factors noted in the above formula are applied in column 5. The results indicate a 0.006 decrease in pre-2018 model year vehicles fatality rates, with declining impacts going forward to model year 2021. In subsequent years, this impact would grow to reflect the both the increased probability that an older vehicle would be involved in crashes with vehicles equipped with advanced technology, as well as the increased technology levels in progressively newer vehicles.[1114] The actual impacts are dynamically calculated within the CAFE Model using updated inputs applicable to this final rule and reflect revised fatality rate trends going forward and cover even older model years. These same adjustments are reflected for nonfatal injuries and PDO crashes.

Table 7-25: Example Adjustment to Fatality Rates of Older Vehicles to Reflect Impact of Advanced Crash Avoidance Technologies in Newer Vehicles

Model Year	MY Fatality Rate	Base Fatality Rate	Difference Base FR - New MY FR	Revised Fatality Rate	% Change	Difference
1995	17.979	8.628	0.269	17.973	0.00034	-0.0062
1996	16.519	8.628	0.269	16.513	0.00038	-0.0062
1997	15.789	8.628	0.269	15.783	0.00039	-0.0062
1998	14.709	8.628	0.269	14.703	0.00042	-0.0062
1999	13.679	8.628	0.269	13.673	0.00045	-0.0062
2000	12.909	8.628	0.269	12.903	0.00048	-0.0062
2001	12.259	8.628	0.269	12.253	0.00051	-0.0062
2002	11.489	8.628	0.269	11.483	0.00054	-0.0062
2003	10.889	8.628	0.269	10.883	0.00057	-0.0062
2004	10.349	8.628	0.269	10.343	0.00060	-0.0062
2005	9.679	8.628	0.269	9.673	0.00064	-0.0062
2006	9.349	8.628	0.269	9.343	0.00066	-0.0062
2007	9.284	8.628	0.269	9.278	0.00067	-0.0062
2008	9.220	8.628	0.269	9.214	0.00067	-0.0062
2009	9.155	8.628	0.269	9.149	0.00068	-0.0062
2010	9.090	8.628	0.269	9.084	0.00068	-0.0062
2011	9.024	8.628	0.269	9.018	0.00069	-0.0062
2012	8.959	8.628	0.269	8.953	0.00069	-0.0062
2013	8.893	8.628	0.269	8.887	0.00070	-0.0062
2014	8.827	8.628	0.269	8.821	0.00070	-0.0062
2015	8.761	8.628	0.269	8.755	0.00071	-0.0062
2016	8.694	8.628	0.269	8.688	0.00071	-0.0062
2017	8.628	8.628	0.269	8.622	0.00072	-0.0062
2018	8.561	8.561	0.202	8.556	0.00054	-0.00466
2019	8.494	8.494	0.135	8.491	0.00037	-0.00311
2020	8.426	8.426	0.068	8.425	0.00018	-0.00156
2021	8.359	8.359	0.000	8.359	0	0

[1114] Table 7-25 was created using inputs from the 2020 CAFE rule NPRM and is provided for explanatory purposes only.

7.3. Impact of Weight Reduction on Safety

Vehicle mass reduction can be one of the more cost-effective means of improving fuel economy, particularly for makes and models not already built with much high-strength steel or aluminum closures or low-mass components. Manufacturers have stated that they will continue to reduce vehicle mass to meet more stringent standards for a given set of vehicle models, and therefore, this expectation is incorporated into the modeling analysis supporting the standards. Newer vehicles incorporate design and hardware improvements that may mitigate some of the direct safety effects to occupants associated with light-weighting.

Historically, as shown in FARS data analyzed by NHTSA,[1115] mass reduction concentrated among the heaviest vehicles (chiefly, the largest light-duty trucks and vans (LTVs), CUVs and minivans) has been estimated to reduce overall fatalities, while mass reduction concentrated among the lightest vehicles (chiefly, smaller passenger cars) has been estimated to increase overall fatalities. Past NHTSA analyses have consistently indicated that increasing the disparity of the masses of vehicles is harmful to safety. In collisions among vehicles, mass reduction in heavier vehicles alone is more beneficial to the occupants of lighter vehicles than it is harmful to the occupants of the heavier vehicles. Mass reduction in lighter vehicles alone is more harmful to the occupants of lighter vehicles than it is beneficial to the occupants of the heavier vehicles. Reducing mass simultaneously across multiple vehicles can have a range of net effects; for example, proportional mass reduction across the vehicle fleet would be expected to have a roughly neutral effect on societal fatality rates for two-vehicle crashes. This highlights the role of mass disparity in societal fatality risk: as the overall vehicle fleet moves closer together is in terms of mass (or, as measured in our analysis, curb weight), the impacts of changes in vehicle mass on fatality risk decrease for crashes involving two or more vehicles. The underlying economics tends toward proportionate mass reduction; in isolation, proportionate mass reduction would reduce mass disparities in the fleet over time. However, even if manufacturers were capable of coordinating and reducing mass equally across all vehicles in the new vehicle fleet, new vehicles would encounter vehicles with different masses within the existing fleet. Further, many fatalities and injuries occur in single-vehicle crashes and collisions between light- and medium-duty vehicles and cyclists or pedestrians; these crash types must also be taken into account in representing the effects of mass reduction on societal fatality rates.

In response to questions of whether designs and materials of more recent MY vehicles may have weakened the historical statistical relationships between mass, size, and safety, NHTSA updated its public database for statistical analysis consisting of crash data. The database incorporates the full range of real-world crash types. NHTSA also sponsored a study conducted by George Washington University (GWU) to develop a fleet simulation model and study the impact and relationship of light-weighted vehicle design with crash injuries and fatalities. That study is discussed in detail in Chapter 7.2.5. The GWU study found results that are directionally consistent with NHTSA's statistical analyses of vehicle mass and fatality risk.

As described below, NHTSA's most recent analysis did not find a statistically significant relationship between mass and safety. This may reflect the effects of a decreased sample size (the most recent study, Puckett and Kindelberger (2016), was based on 32 percent fewer fatal cases than the Kahane 2012 study) as well as possible mitigating effects from newer safety technologies or vehicle designs. While not finding statistical significance, NHTSA's current study did find results that are directionally consistent with previous NHTSA studies and the GWU fleet simulation. The common pattern across all studies is that changes in mass

[1115] Kahane, C. J. 1997. Relationships Between Vehicle Size and Fatality Risk in Model Year 1985-93 Passenger Cars and Light Trucks. NHTSA Technical Report. DOT HS 808 570. National Highway Traffic Safety Administration: Washington, D.C. Available at: https://rosap.ntl.bts.gov/view/dot/8727. (Accessed: Feb. 16, 2024); Kahane, C. J. 2003. Vehicle Weight, Fatality Risk and Crash Compatibility of Model Year 1991-99 Passenger Cars and Light Trucks. NHTSA Technical Report. DOT HS 809 662. National Highway Traffic Safety Administration: Washington, D.C. Available at: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/809662. (Accessed: Feb. 16, 2024); Kahane, C. J. 2010. Relationships Between Fatality Risk, Mass, and Footprint in Model Year 1991-1999 and Other Passenger Cars and LTVs. Final Regulatory Impact Analysis: Corporate Average Fuel Economy for model year 2012-MY 2016 Passenger Cars and Light Trucks. National Highway Traffic Safety Administration: Washington, D.C. pp. 464–542. Available at: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/811665. (Accessed: May 31, 2023); Kahane, C.J. 2012. Relationships Between Fatality Risk, Mass, and Footprint in Model Year 2000-2007 Passenger Cars and LTVs: Final Report, NHTSA Technical Report. National Highway Traffic Safety Administration: Washington, D.C. Report No. DOT-HS-811-665; Puckett, S.M., Kindelberger, J.C. 2016. Relationships between Fatality Risk, Mass, and Footprint in Model Year 2003-2010 Passenger Cars and LTVs – Preliminary Report. Docket No. NHTSA2016-0068. National Highway Traffic Safety Administration: Washington, D.C.

disparity are associated with changes in motor vehicle safety: increased disparity increases fatality risk, while decreased disparity decreases risk.

The CAFE standards for light-duty vehicles detailed here are "footprint-based," with footprint being defined as a measure of a vehicle's size, roughly equal to the wheelbase times the average of the front and rear track widths. Manufacturers are less likely than they were in the past to reduce vehicle footprint to reduce mass for increased fuel economy. Indeed, as reflected in shifts from smaller passenger cars to larger trucks, SUVs, and CUVs (see Chapter 1.2.3) the average footprint of light-duty vehicles (and the most-common pickups with GVWR above 8,500 pounds) has increased slightly and gradually since the adoption of footprint-based standards. Footprint-based standards create a disincentive for manufacturers to produce smaller-footprint vehicles. This is because, as historically structured, fuel economy targets become more stringent as footprint decreases. The agency believes that the shape of the footprint curves themselves is such that the curves should neither encourage manufacturers to increase the footprint of their fleets, nor to decrease it. Several technologies, such as substitution of light, high-strength materials for conventional materials during vehicle redesigns, have the potential to reduce weight and conserve fuel while maintaining a vehicle's footprint.

For the rulemaking analysis, the CAFE Model tracks the amount of mass reduction applied to each vehicle model, and then applies estimated changes in societal fatality risk per 100 pounds of mass reduction determined through the statistical analysis of FARS crash data. 100-pound mass reductions have been considered in NHTSA analyses as a matter of convention; the implications of the analysis would not change meaningfully either for focal vehicle classes or for the fleet at large (i.e., in terms of mass disparity) if different magnitudes of mass reduction were considered. This process allows the CAFE Model to tally changes in fatalities attributed to mass reduction across all the analyzed future model years. In turn, the CAFE Model is able to provide an overall impact of the final rule and alternatives on fatalities attributed to changes in mass disparity resulting from mass reduction. The projections of societal effects of mass reduction from the CAFE Model are subject to uncertainty in the paths that manufacturers will follow in applying mass reduction to the fleet. That is, there is uncertainty in which vehicle models will undergo mass reduction. Rather, the model is calibrated to incorporate the best available information on the application, and safety effects, of mass reduction.

7.3.1. Historical Analysis of Vehicle Mass and Safety

The methodology used for the statistical analysis of historical crash data has evolved over many years. The methodology used for this final rule is carried forward from the 2020 and 2022 CAFE rules, and reflects learnings and refinements from: NHTSA studies in 2003, 2010, 2011, 2012, and 2016; independent peer review of 23 studies by UMTRI; two public workshops hosted by NHTSA; interagency collaboration among NHTSA, DOE and EPA; and comments to CAFE and GHG rulemakings in 2010, 2012, the 2016 Draft TAR, and the 2020 rulemaking. As explained in greater detail below, the methodology used for the statistical analysis of historical crash data for this final rule is the best and most up-to-date available.

Over the course of refining the methodology and the corresponding data per stakeholder feedback and internal review, NHTSA has confirmed the central relationship that mass reduction is most likely to reduce societal fatalities when concentrated among the heaviest vehicles. For crashes involving two or more vehicles, this relationship manifests itself within the vehicle fleet in terms of the dispersion of vehicle mass (or curb weights): All else being equal, as disparities in mass among vehicles increase, fatalities increase as well. That is, mass reduction concentrated among the lightest vehicles would increase the dispersion of mass (i.e., the heaviest vehicles become even heavier than the lightest vehicles), while mass reduction concentrated among the heaviest vehicles would decrease the dispersion of mass (i.e., the lightest vehicles grow closer in mass to the heaviest vehicles). For single-vehicle crashes and crashes with pedestrians, cyclists, and motorcycles, relationships between mass and fatality risk vary across both crash type and vehicle class. As in the preceding analyses supporting CAFE rulemaking, each of these estimated relationships is represented in overall estimates of societal impacts of changes in curb weight on fatalities for each vehicle class, weighted by the estimated shares of each crash type.

Representing the overall relationship of mass reduction and safety within the CAFE Model (e.g., through model coefficients placing a detrimental effect on mass reduction in the lightest vehicles and a beneficial effect on mass reduction in the heaviest vehicles) enables the model to project effects of mass reduction in individual vehicle models on societal fatalities. The model achieves this by incorporating the corresponding effects of vehicle-model-specific mass reduction on the dispersion of mass for multi-vehicle crashes and effects of mass reduction on other types of crashes across the vehicle fleet.[1116] Projected levels of mass reduction are internal to the CAFE Model and represent plausible paths forward for manufacturers to meet fuel economy targets in an economical manner, rather than specific predictions on mass reduction paths. Thus, there is some uncertainty introduced by the use of CAFE Model estimates as predictions of future changes in the distribution of vehicle mass. Consistency in the directionality and magnitude of the central point estimates across NHTSA's analyses has increased NHTSA's confidence that reducing the dispersion of mass across the vehicle fleet would reduce societal fatalities.

Researchers have been using statistical analysis to examine the relationship of vehicle mass and safety in historical crash data for many years and continue to refine their techniques. In the model year 2012-2016 final rule, NHTSA stated we would conduct further study and research into the interaction of mass, size, and safety to assist future rulemakings and start to work collaboratively by developing an interagency working group between NHTSA, EPA, DOE, and CARB to evaluate all aspects of mass, size, and safety. The team would seek to coordinate government- supported studies and independent research to the greatest extent possible to ensure the work is complementary to previous and ongoing research and to guide further research in this area.

Subsequent to the publication of the model year 2012-2016 rule, NHTSA identified three specific areas to direct research in preparation for future CAFE rulemakings. First, NHTSA would contract with an independent institution to review the statistical methods NHTSA and DRI used to analyze historical data related to mass, size, and safety, and to provide recommendations on whether existing or other methods should be used for future statistical analysis of historical data.

In 2010, NHTSA published the results of the contractor's review in a research report (hereinafter 2010 Kahane report). The 2010 Kahane report considered the potential near multicollinearity in the historical data and suggested methods to overcome it in a logistical regression analysis. The 2010 Kahane report was also peer reviewed by two other experts in the safety field - Farmer (Insurance Institute for Highway Safety) and Lie (Swedish Transport Administration) prior to publication.

Second, NHTSA and EPA, in consultation with DOE, would update the model year 1991–1999 database, used to calculate the mass safety coefficients, with newer vehicle data and create a common database that could be made publicly available to address concerns that differences in data were leading to different results in statistical analyses by different researchers. The database contains FARS and State-level crash data, to enable the estimation of changes in fatality risk as a function of vehicle curb weight across recent light-duty vehicle models. The FARS component of the database essentially forms the numerator of fatality risk calculations (i.e., societal fatalities), while the State component of the database forms the denominator (i.e., VMT by vehicle model). The FARS component of the database represents a census of fatalities associated with vehicle models in the sample; the State component of the database represents a random sample of vehicle exposure (i.e., induced exposure, comprised of crashes where drivers are assumed to be not at fault), yielding estimates of distributions of key contextual factors, such as driver age, driver sex, and vehicle location. Combining these data within a logistic regression yields a range of estimated fatality risks (i.e., fatalities per VMT) for each vehicle model, which vary with respect to vehicle curb weight, footprint, and contextual effects. This enables the logistic regression to isolate effects associated with curb weight, yielding the estimates of primary interest for the analysis summarized in this subchapter.

And third, NHTSA sought to identify vehicles using newer material substitution and smart design and to assess if there were sufficient crash data involving those vehicles for statistical analysis to assess if modern mass reduction methods affected the historical relationship between vehicle mass, size, and safety. If sufficient data existed, statistical analysis would be conducted to compare the relationship among mass, size, and safety of these smart design vehicles to vehicles of similar size and mass with more traditional designs.

[1116] There are nine types of crashes specified in the mass-safety analysis: three types of single-vehicle crashes, five types of two-vehicle crashes; and one classification of all other crashes. Single-vehicle crashes include first-event rollovers, collisions with fixed objects, and collisions with pedestrians, bicycles and motorcycles. Two-vehicle crashes include collisions with: heavy-duty vehicles; cars, CUVs, or minivans, truck-based LTVs. All other fatal crash types include collisions involving more than two vehicles, animals, trains and other crash types.

By the time of the model year 2017-2025 final rule, significant progress had been made on these tasks. The independent review of then-recent statistical analyses of the relationship between vehicle mass, size, and crash fatality rates had been completed by UMTRI. Led by Dr. Green, UMTRI evaluated more than 20 academic papers, including studies done by NHTSA's Kahane, Wenzel of the U.S. Department of Energy's Lawrence Berkeley National Laboratory (LBNL), Dynamic Research, Inc., and others. UMTRI's basic findings will be discussed below.

To support rulemaking efforts, NHTSA created a common, updated database for statistical analysis consisting of crash data of model years 2000-2007 vehicles in calendar years 2002- 2008, as compared to the database used in prior NHTSA analyses, which was based on model years 1991–1999 vehicles in calendar years 1995-2000. The new database was the most up-to- date possible, given the processing lead time for crash data and the need for enough crash cases to permit statistically meaningful analyses. NHTSA made the preliminary version of the new database, which was the basis for NHTSA's 2011 preliminary report (hereinafter 2011 Kahane report), available to the public in May 2011, and an updated version in April 2012 (used in NHTSA's 2012 final report, hereinafter 2012 Kahane report), enabling other researchers to analyze the same data and hopefully minimize discrepancies in results because of inconsistencies across databases. NHTSA updated the crash and exposure databases for the 2016 Draft TAR analysis and added a new variable denoting status as a medium- or heavy-duty truck to the database accompanying starting with the 2021 NPRM.

NHTSA was aware of several studies that had been initiated using the 2011 version or the 2012 version of NHTSA's newly established safety database. In addition to new Kahane studies, other recent and on-going studies included two by Wenzel at LBNL under contract with the U.S. DOE and one by DRI contracted by ICCT. These studies took somewhat different approaches to examining the statistical relationship between fatality risk, vehicle mass, and size. In addition to a detailed assessment of the 2011 Kahane report, Wenzel considered the effect of mass and footprint reduction on casualty risk per crash, using data from 13 states. Casualty risk includes fatalities and serious or incapacitating injuries. Both LBNL studies were peer reviewed and subsequently revised and updated. DRI used models separating the effect of mass reduction on two components of fatality risk - crash avoidance and crashworthiness. The LBNL and DRI studies were available in the docket for the 2012 final rule.

For the 2020 CAFE rule, the crash and exposure databases were updated again; these databases were used to support this final rule as well. The databases were updated to include crash data for model year 2004-2011 vehicles during calendar years 2006-2012; for ensuing rulemakings, NHTSA intends to once again update the databases with more recent model years and calendar years, where feasible. As in previous analyses, NHTSA has made the databases available to the public on its website.[1117]

NHTSA has continued to sponsor new studies and research to inform the current CAFE rulemaking. In addition, the NAS/National Academies of Sciences, Medicine, and Medicine (NASEM) published reports that include discussions of relationships between vehicle mass and societal fatality risk.[1118] The 2015 NAS report summarizes results from studies by NHTSA, DRI, and LBNL, confirming the general relationships between vehicle mass disparity and societal fatality risk (i.e., mass reduction in the lightest vehicles is detrimental, mass reduction on in the heaviest vehicles is beneficial) and noting that future changes in technology and fleet composition could lead to different conclusions. The 2021 NASEM report highlights the role that mass disparity among the vehicle fleet plays in societal fatality risk, with greater mass disparity associated with greater societal fatality risk. The NASEM report clarifies that the path of mass disparity is unknown (i.e., general trends and the application of mass reduction technologies could increase or decrease mass disparity). The NASEM report qualifies the general conclusions associated with mass disparity, noting that new vehicle designs, continued effects associated with footprint-based fuel economy standards, changes in demand across vehicle classes, and increased demand for vehicles with (heavier) electrified powertrains could yield different safety relationships from those identified in relevant studies. In establishing standards, all

[1117] Visit https://www.nhtsa.gov/content/nhtsa-ftp/191, for access to the databases and other files and documentation associated with CAFE rulemaking.
[1118] National Research Council. 2015. Cost, Effectiveness, and Deployment of Fuel Economy Technologies for Light-Duty Vehicles. *The National Academies Press*: Washington, D.C. Available at: https://nap.nationalacademies.org/21744/. (Accessed: May 31, 2023); National Academies of Sciences, Medicine, and Engineering. 2021. Assessment of Technologies for Improving Light-Duty Fuel Economy 2025-2035. *The National Academies Press:* Washington, D.C. Available at: : https://doi.org/10.17226/26092/. (Accessed: May 31, 2023).

available data, studies, and objective information without regard to whether they were sponsored by NHTSA, will be considered.

Undertaking these tasks has helped come closer to resolving ongoing debates in statistical analysis research of historical crash data and has informed NHTSA analysis supporting this final rule. It is intended that these conclusions will continue to be applied going forward in future rulemaking, and it is believed the research will assist the public discussion of the issues.

7.3.1.1. 2011 NHTSA Workshop on Vehicle Mass, Size, and Safety

On February 25, 2011, NHTSA hosted a workshop on mass reduction, vehicle size, and fleet safety at the Headquarters of the U.S. Department of Transportation in Washington, D.C. The purpose of the workshop was to provide a broad understanding of current research in the field and provide stakeholders and the public with an opportunity to weigh in on this issue. NHTSA also created a public docket to receive comments from interested parties who were unable to attend.

Speakers included Kahane of NHTSA, Wenzel of LBNL, Van Auken of DRI, Padmanaban of JP Research, Inc., Lund of the Insurance Institute for Highway Safety, Green of UMTRI, Summers of NHTSA, Peterson of Lotus Engineering, Kamiji of Honda, German of ICCT, Schmidt of the Alliance of Automobile Manufacturers, Nusholtz of Chrysler, and Field of the Massachusetts Institute of Technology.

The wide participation in the workshop allowed the agency to hear from a broad range of experts and stakeholders. Contributions were particularly relevant to the analysis of effects of mass reduction for the model year 2017-2025 final rule. Presentations were divided into two sessions addressing two expansive sets of issues - statistical evidence of the roles of mass and size on safety, and engineering realities regarding structural crashworthiness, occupant injury, and advanced vehicle design. Some main points from the workshop were:

1. Statistical studies of crash data attempting to identify relative recent historical effects of vehicle mass and size on fleet safety show complicated relationships with many confounding influences in data.
2. Analyses must control for individual technologies with significant safety effects (e.g., Electronic Stability Control, airbags).
3. The physics of a two-vehicle crash require the lighter vehicle experience a greater change in velocity, which, all else being equal, often leads to disproportionately more injury risk.
4. The separation of key parameters is a challenge to analyses, as vehicle size has historically been highly correlated with vehicle mass.
5. No consensus on whether smaller, lighter vehicles maneuver better, and thus avoid more crashes, than larger, heavier vehicles.
6. Kahane's results from his 2010 report found a scenario, which took some mass out of heavier vehicles but little or no mass out of the lightest vehicles, did not affect safety in absolute terms, and noted if analyses were able to consider the mass of both vehicles in a two-vehicle crash, results may be more indicative of future crashes.

7.3.1.2. UMTRI Report

NHTSA contracted with UMTRI to conduct an independent review of a set of statistical analyses of relationships between vehicle curb weight, footprint variables (track width, wheelbase), and fatality rates from vehicle crashes. The purpose of this review was to examine analysis methods, data sources, and assumptions of statistical studies, with the objective of identifying reasons for any differences in results. Another objective was to examine the suitability of various methods for estimating fatality risks of future vehicles.

UMTRI reviewed a set of papers, reports, and manuscripts provided by NHTSA (listed in Appendix A of UMTRI's report881) examining statistical relationships between fatality or casualty rates and vehicle properties such as curb weight, track width, wheelbase, and other variables.

Fundamentally, the UMTRI team concluded the database created by Kahane appeared to be an impressive collection of files from appropriate sources and the best ones available for answering the research questions considered in this study; the disaggregate logistic regression model used by NHTSA in its 2003 report (hereinafter 2003 Kahane report) seemed to be the most appropriate model, valid for the analysis in the context that it was used - finding general associations between fatality risk and mass, and general directions of reported associations were correct.

7.3.1.3. 2012 LBNL Reports

In its 2012 "Phase 1" report, LBNL replicated the 2012 NHTSA baseline results and conducted 19 alternative regression models to test the sensitivity of the NHTSA baseline model to changes in the measure of risk, variables included, and data used. In its report, LBNL pointed out that other vehicle attributes, driver characteristics, and crash circumstances were associated with much larger changes in risk than mass reduction. LBNL also demonstrated there was little correlation between mass and fatality risk by vehicle model, even after accounting for all other vehicle attributes, driver characteristics, and crash circumstances.

In its 2012 "Phase 2" report, LBNL used data from police reported crashes in the 13 states to study casualty (fatality plus severe injury) risk per VMT, and to divide risk per VMT into its two components - crash frequency (crashes per VMT) and crashworthiness/crash compatibility (risk per crash). LBNL found mass reduction was associated with increases in crash frequency and decreases in fatality or serious injury risk per crash. This finding is inconsistent with the hypothesis that increased mass is protective in a crash. Decreased fatality and serious injury risk associated with decreased mass could be indicative of multiple factors, including the role of mass disparity in the fleet (i.e., although decreased mass increases fatality risk for a vehicle's occupants, the offsetting effect for occupants of crash partner vehicles could be larger, on average), and statistical limitations (e.g., omitted variables bias). Preliminary versions LBNL's Phase 1 and Phase 2 reports were reviewed by external reviewers, and comments were incorporated into final versions published in 2012.[1119,1120]

7.3.1.4. 2012 DRI Reports

DRI published three preliminary reports in 2012. DRI's preliminary Phase I report updated its analysis of data from 1995 to 2000 and was able to replicate results from the 2003 Kahane report. DRI's preliminary Phase II report replicated the 2012 rulemaking baseline results and used a simultaneous two-stage model to estimate separate effects of mass reduction on crash frequency and fatality risk per crash. Results from DRI's two-stage model were comparable to LBNL's Phase 2 analysis - mass reduction was associated with increases in crash frequency and decreases in risk per crash. DRI's preliminary summary report showed the effect of two alternative regression models - using stopped rather than non-culpable vehicles as the basis for the induced exposure database and replacing vehicle footprint with its component's wheelbase and track width. Under these two alternatives, mass reduction was estimated to have less harmful (e.g., for the lightest passenger cars) or more beneficial (e.g., for the heaviest LTVs) impacts on societal fatality risk. The three preliminary DRI reports were peer-reviewed with comments incorporated into the final versions published in 2013.

Results from LBNL's Phase 2 and DRI's Phase II reports implied the increase in fatality risk per VMT from mass reduction in lighter cars estimated by the NHTSA baseline model was because of increasing crash frequency and not increasing fatality risk once a crash had occurred, as mass was reduced. In the 2012 Kahane report, NHTSA argued effects of crash frequency could not be separated from risk per crash because of reporting bias in state crash data, such as lack of a crash severity measure, and possible bias because of underreporting of less severe crashes in certain states. This is a complex issue, in which it is possible for crashes to be reported at variable rates across vehicle type, vehicle size, or vehicle weight. That is, if underreporting were solely random, it may be feasible to draw unbiased inferences with respect to crash risk

1119 Green, P.E. et al. 2011. Independent Review Statistical Analyses of Relationship between Vehicle Curb Weight, Track Width, Wheelbase and Fatality Rates. Report for U.S. Department of Transportation, Report No. UMTRI-2011-12. Available in the docket to the MY 2017-2025 rulemaking at regulations.gov, or at https://deepblue.lib.umich.edu/bitstream/handle/2027.42/85162/102752.pdf?sequence=1&isAllowed=y. (Accessed: Feb. 16, 2024).
1120 Wenzel, T.P. 2012. Lawrence Berkeley National Laboratory Report. An Analysis of the Relationship between Casualty Risk Per Crash and Vehicle Mass and Footprint for Model Year 2000-2007 Light-Duty Vehicles. (Final Report). No. LBNL-5697E. Berkeley, CA. pp. 1-95. Available at: https://www.epa.gov/sites/default/files/2016-11/documents/lbnl-2012-phase-2.pdf.; Wenzel T.P. 2012. Assessment of NHTSA's Report. Relationships Between Fatality Risk, Mass, and Footprint in Model Year 2000-2007 Passenger Cars and LTVs. (Final Report). Lawrence Berkeley National Laboratory Report No. LBNL-5698E. Washington, D.C. pp. 1-23. Analyzing Casualty Risk using State Data on Police-Reported Crashes. Available at: https://eta-publications.lbl.gov/sites/default/files/lbnl-2001137.pdf. (Accessed: May 31, 2023).

and crash severity independently. However, if underreporting is not random (e.g., crashes involving smaller, lighter, or older, less valuable vehicles may be less likely to meet State reporting thresholds), factors leading to variable reporting rates would be conflated with representations of crash frequency.

7.3.1.5. 2013 NHTSA Workshop on Vehicle Mass, Size and Safety

On May 13-14, 2013, NHTSA hosted a follow-on symposium to continue exploring relevant issues and concerns with mass, size, and potential safety tradeoffs, bringing together experts in the field to discuss questions to address CAFE standards for model years 2022-2025. The first day of the two-day symposium focused on engineering, while the second day investigated various methodologies for assessing statistical evidence of roles of vehicle mass and size on occupant safety.

Speakers for the second day, focusing on the subject matter of this chapter, included Kahane of NHTSA, Nolan of the Insurance Institute for Highway, Nusholtz of Chrysler, Van Auken of Dynamic Research Incorporated, and Wenzel of LBNL.

Summaries of the topics follow:

1. Kahane gave an overview of statistical studies designed to determine the incremental change in societal risk as vehicle mass of a particular vehicle is modified while keeping its footprint (the product of wheelbase and track width) constant. The physics of crashes, in particular conservation of momentum and equal and opposite forces, implies mass reduction in the heaviest vehicles and/or mass increase in the lightest vehicles can reduce societal risk in two-vehicle crashes. It is, therefore, reasonable that reducing disparities in mass ratio in the vehicle fleet (such as by reducing the mass of heavy vehicles by a larger percentage than that of light vehicles) should reduce societal harm. This trend was noticed in data for model year 2000-2007 vehicles but only statistically significant for the lightest group of vehicles. This is similar to results found for model year 1991-1999 vehicles in a 2003 study. Kahane acknowledged numerous confounding factors such as maneuverability of different vehicle classes (although data indicated smaller cars were more likely to be involved in crashes), driver attributes and vulnerabilities, advances in restraint safety systems and vehicle structures, and electronic stability control.
2. Wenzel replicated Kahane's results using the same data and methods but came to slightly different conclusions. Wenzel demonstrated that the effect of mass or footprint reduction estimated on societal risk is much smaller than the effect estimated for other vehicle attributes, driver characteristics, or crash circumstances. Wenzel plotted actual fatality risk versus weight by vehicle make and model and estimated predicted risk by make and model after accounting for all control variables used in NHTSA's baseline model except for mass and footprint. The remaining, or residual risk, not explained by the control variables has no correlation with vehicle weight. Wenzel presented results of the 19 alternative regression models he conducted to test the sensitivity of results from NHTSA's baseline model. He also presented results from LBNL's Phase 2 analysis, which examined the effect of mass or footprint reduction on the two components of risk per VMT - crashes per VMT (crash frequency), and risk per crash (crashworthiness). His analysis of casualty risk using crash data from 13 states and his replication of the DRI two-state simultaneous regression model indicate mass reduction is associated with an increase in crash frequency but a decrease in risk per crash.
3. Van Auken also replicated Kahane's results from the NHTSA baseline model and presented results from three sensitivity regression models. Replacing footprint with its components – wheelbase and track width – reduces the estimated increase in risk from mass reduction in cars and suggests reduction in light trucks decreases societal risk. Using stopped rather than non-culpable vehicles to derive the induced exposure dataset also reduces the estimated increase in risk from mass reduction in lighter-than-average cars and light trucks and estimates mass reduction in heavier cars and trucks decreases societal risk. Adding these changes to the NHTSA baseline model greatly reduces the estimated increase in risk from mass reduction in the lightest cars and is associated with decreases in risk for all other vehicle types. Van Auken described in more detail his two- stage simultaneous regression model, which allows risk per vehicle mile of travel to be decomposed into crashes per VMT (crash frequency) and risk per crash (crashworthiness/ crash compatibility). As with Wenzel's analysis, Van Auken found mass reduction is associated with an increase in crash frequency but with a decrease in risk per crash. Once again, resulting trends were similar to those from Kahane and Wenzel. Van Auken explored the issue of inducing the exposure of vehicles via crash statistics in which relative exposure was measured by non-

culpable vehicles in the crash database versus by its subset of stopped vehicles in the data and also investigated the effect of substituting footprint for track width and wheelbase as size variables in the regression.

4. Nusholtz of Chrysler presented an analysis of the sensitivity of the fleet-wide fatality risk to changes in vehicle mass and size. He noted the difficulty in finding a definitive metric for "size." He dismissed some assertions of mass having negligible (or purely negative) effects on safety as leading to absurd conclusions in the extreme. He extended the methods of Joksch (1993) and Evans (1992) to estimate risk as a function of readily measurable vehicle attributes and reported crash characteristics. He used crash physics (closing speed, estimates of inelastic stiffness, and energy absorption) to estimate changes in fleet risk as a function of changes in these parameters. He observed mass is a dominant factor but believed crush space could begin to dominate if vehicles could be made larger. Nusholtz concurred removing more mass from larger vehicles could reduce risk but is not convinced such a strategy will be sufficient to meet fuel economy goals. He regards safety implications of mass reduction to be transition issues of greater importance so long as legacy heavier vehicles are used in significant numbers.
5. Nolan analyzed historical trends in the fleet. While median vehicle mass has increased, safety technologies have enhanced the safety of current small cars to the level only achieved by larger cars in the past. In particular, electronic stability control has reduced the relative importance of some severe crash modes. While acknowledging that smaller vehicles will always be at a disadvantage, there is hope further technological advances such as crash avoidance systems hold promise in advancing safety. Fleet safety would be enhanced if these technologies could quickly penetrate across the fleet to small cars as well as large ones.
6. Nusholtz presented the results of an attempt to separate the effect of mass on crash outcome as distinct from the likelihood of the crash itself. It was acknowledged mass can affect both. Nusholtz emphasized crash parameters (e.g., closing speed) necessarily dominate. Kahane suggested reporting rates might be sufficiently different to affect results. Nusholtz cautioned physics and statistics must be considered but, in a way, connecting them to reality rather than abstractions. Nusholtz noted assessments of that effect are difficult because determining when and why a crash did not occur is problematic against the backdrop of confounding information.

7.3.1.6. Subsequent Analysis by LBNL

As part of its review of the 2012 DRI studies, LBNL recreated DRI's two-stage simultaneous regression model, which estimated the effect of mass or footprint reduction on the two components of fatality risk per VMT - number of crashes per VMT and risk of fatality per crash. LBNL first replicated DRI's methodology of taking a random "decimated" sample of crash data from 10 states for induced exposure records. Although LBNL was not able to exactly recreate DRI's results, its results were comparable to DRI's, and LBNL's Phase 2, analysis. That is, mass reduction is associated with - (1) increases in crash frequency for all vehicle types; and (2) with decreases in fatalities per crash for all vehicle types except heavier cars. LBNL then re-ran the two-stage regression model using all crash data from the 13 states NHTSA used in their baseline model and obtained similar results.

The LBNL Phase 2 study and DRI Phase II study had two unexpected results - mass reduction is associated with increased crash frequency but decreased risk per crash, and signs on some of the control variables are in the unexpected direction. Mass reduction could feasibly reduce crash risk due to increased maneuverability and braking capability; the converse result may reflect driver behavior (e.g., riskier maneuvers under higher power-to-weight ratios) or important structural changes under light-weighting. Examples of unexpected signs for control variables include - side airbags in light trucks and CUVs/minivans were estimated to reduce crash frequency; the crash avoidance technologies ESC and antilock braking systems (ABS) were estimated to reduce risk once a crash had occurred; and all-wheel- drive and brand-new vehicles were estimated to increase risk once a crash had occurred. In addition, male drivers were estimated to have essentially no effect on crash frequency but were associated with a statistically significant increase in fatality risk once a crash had occurred. In addition, driving at night, on high-speed or rural roads, was associated with higher increases in risk per crash than on crash frequency.

A possible explanation for these unexpected results is that important control variables were not included in regression models. For example, crashes involving male drivers, in vehicles equipped with AWD, or occurring at night on rural or high-speed roads, may not be more frequent but are rather more severe than other crashes, leading to greater fatality or casualty risk. Drivers who select vehicles with certain safety features may tend to drive more carefully, resulting in vehicle safety features designed to improve crashworthiness or compatibility, such as side airbags, and are associated with lower crash frequency.

LBNL made several attempts to create a regression model that “corrected” for these unexpected results. LBNL first examined results of three vehicle braking and handling tests conducted by Consumer Reports - the maximum speed achieved during the avoidance maneuver test, acceleration time from 45 to 60 mph, and dry braking distance.

When these three test results were added to the LBNL baseline regression model of the number of crashes per mile of vehicle travel in cars, none of the three handling/braking variables had the expected effect on crash frequency. In other words, an increase in maximum maneuver speed, the time to reach 60 miles per hour, or braking distance on dry pavement in cars, either separately or combined, was associated with a decrease in the likelihood of a crash, of any type or with a stationary object. Adding one or all of the three handling/braking variables had relatively little effect on the estimated relationship between mass or footprint reduction in cars and crash frequency, either in all types of crashes or only in crashes with stationary objects.

LBNL next tested the sensitivity of the relationship between mass or footprint reduction and crash frequency by adding five additional variables to the regression models - initial vehicle price, average household income, bad driver rating, alcohol/drug use, and seat belt use. An increase in vehicle price, household income, or belt use was associated with a decrease in crash frequency, while an increase in alcohol/drug use was associated with an increase in crash frequency, for all three vehicle types; a poor bad driver rating increases crash frequency in cars, but unexpectedly decreases crash frequency in light trucks and CUVs/minivans. Including these five variables, either individually or including all in the same regression model, did not change general results of the baseline LBNL regression model - mass reduction is associated with an increase in crash frequency in all three types of vehicles, while footprint reduction is associated with an increase in crash frequency in cars and light trucks but with a decrease in crash frequency in CUVs/ minivans. The variable with the biggest effect was initial vehicle purchase price, which dramatically reduced the estimated increase in crash frequency in heavier-than- average cars (and in heavier-than-average light trucks, and all CUVs/minivans). These results suggest other, subtler, differences in vehicles and their drivers account for the unexpected finding that lighter vehicles have higher crash frequencies than heavier vehicles for all three types of vehicles.

In the 2012 Kahane report NHTSA suggested two possible explanations for unexpected results in the LBNL Phase 2 analysis and the DRI and LBNL two-stage regression models – the analyses did not account for the severity of the crash, and there was possible bias in the crashes reported to police in different states, with less severe crashes being under-reported for certain vehicle types. LBNL analyzed the first of Kahane’s explanations for the unexpected result of mass reduction being associated with decreased risk per crash, by re-running the baseline Phase 2 regressions after excluding the least-severe crashes from the state crash databases objects. Only vehicles described as “disabled” or as having “severe” damage were included, while vehicles driven away from the crash site or that had functional, none, or unknown damage were excluded. Excluding non-severe crashes had little effect on the relationship between mass reduction and crash frequency; in either LBNL’s Phase 2 baseline model or the two-stage simultaneous model - mass reduction was associated with an increase in crash frequency and a decrease in risk per crash. Excluding the non-severe crashes also did not change unexpected results for other control variables - most of the side airbag variables and the crash compatibility variables in light trucks, continued to be associated with an increase in crash frequency, while ABS, electronic stability control, AWD, male drivers, young drivers, and driving at night, in rural counties, and on high-speed roads continued to be associated with an increase in risk per crash.

DOE contracted with Wenzel of LBNL to conduct an assessment of NHTSA’s updated 2016 study of the effect of mass and footprint reductions on U.S. fatality risk per VMT (LBNL 2016 “Phase 1” preliminary report), and to provide an analysis of the effect of mass and footprint reduction on casualty risk per police-reported crash, using independent data from 13 states (LBNL 2016 “Phase 2” preliminary report).

The 2016 LBNL Phase 1 report replicated the analysis in NHTSA’s 2016 report (hereinafter, 2016 Puckett and Kindelberger report), using the same data and methods, and in many cases using the same SAS programs, to confirm NHTSA's results. The LBNL report confirmed NHTSA's 2016 finding, holding footprint constant, each 100-lbs of mass reduction is associated with a 1.49 percent increase in fatality risk per VMT for cars weighing less than 3,197 pounds, a 0.50 percent increase for cars weighing more than 3,197 pounds, a 0.10 percent decrease in risk for light trucks weighing less than 4,947 pounds, a 0.71 percent decrease in risk for light trucks weighing more than 4,947 pounds, and a 0.99 percent decrease in risk for CUVs/minivans.

Wenzel tested the sensitivity of model estimates to changes in the measure of risk as well as control variables and data used in the regression models. Wenzel concluded there is a wide range in fatality risk by vehicle model for models possessing comparable mass or footprint, even after accounting for differences in drivers' age and gender, safety features installed, and crash times and locations.

The 2016 LBNL Phase 1 report notes many of the control variables NHTSA includes in its logistic regressions are statistically significant and have a much larger estimated effect on fatality risk than vehicle mass. For example, installing torso side airbags, electronic stability control, or an ABS in a car was estimated to reduce fatality risk by at least 7 percent; cars driven by men were estimated to have a 40 percent higher fatality risk than cars driven by women; and cars driven at night, on rural roads, or on roads with a speed limit higher than 55 mph were estimated to have a fatality risk over 100 times higher than cars driven during the daytime on low-speed non-rural roads. The report concluded that, while the estimated effect of mass reduction may result in a statistically-significant increase in risk in certain cases, the increase is small and is overwhelmed by other known vehicle, driver, and crash factors.

7.3.1.7. Presentation to NAS Subcommittee

Kahane, Wenzel, Ridella, Thomas of Honda, and Nolan of IIHS, were invited to the June 2013 NAS subcommittee on light-duty fuel economy to present results from their 2012 analyses. At the meeting, committee members raised several questions about the studies; presenters responded to these questions at the meeting, as well as in two emails in August 2013 and December 2014.

7.3.1.8. 2015 NAS Report

In 2015, the NAS published the report "Cost, Effectiveness and Deployment of Fuel Economy Technologies for Light-Duty Vehicles." The report is the result of the work of the Committee on Assessment of Technologies for Improving the Fuel Economy of Light-Duty Vehicles, Phase 2, established upon the request of NHTSA to help inform the midterm review. The committee was asked to assess the CAFE standard program and the analysis leading to the setting of standards, as well as to provide its opinion on costs and fuel consumption improvements of a variety of technologies likely to be implemented in the light- duty fleet between now and 2030.

The Committee found the estimates of mass reductions to be conservative for cars; the Committee projected mass reductions between 5 percent (for small and large cars) and 6.5 percent (for midsize cars) larger than the projections. The Committee acknowledged the possibility of negative safety effects during the transition period because of variances in how reductions occurred. Because of this, the Committee recommended NHTSA consider and, if necessary, take steps to mitigate this possibility.

7.3.1.9. National Bureau of Economic Research (NBER) Working Paper

In a National Bureau of Economic Research (NBER) working paper, Bento et al. (2017) presents an analysis of relationships among traffic fatalities, CAFE standards, and distributions of model year 1989-2005 light-duty vehicle curb weights. Consistent with NHTSA's mass-size-safety analyses, Bento et al. concluded decreases in the dispersion of curb weights have a positive effect on safety. A central conclusion in Bento et al. is the monetized value of the net safety improvements achieved under CAFE exceed costs of meeting CAFE standards (i.e., CAFE offers a positive net societal benefit independent of fuel- related impacts). However, NHTSA identified factors in the analysis limiting the inference that can be drawn with respect to CAFE rulemaking going forward. The temporal range of the analysis does not include current footprint-based standards that incentivize light-weighting existing models rather than switching to lighter models. The statistical approach in the analysis did not account for the rebound effect or effects of CAFE on vehicle sales (which affect per-mile fatality risk), and Bento et al. also represented annual CAFE compliance costs at a level substantially less than expected to comply with standards.

7.3.2. Recent NHTSA Analysis Supporting CAFE Rulemaking

As mentioned previously, NHTSA and EPA's 2012 joint final rule for model year 2017 and beyond set "footprint-based" standards, with footprint being defined as roughly equal to the wheelbase multiplied by the average of the front and rear track widths. Basing standards on vehicle footprint is intended to discourage manufacturers from downsizing their vehicles because fuel economy targets are contingent on the vehicles size—the smaller the vehicle's footprint, the higher (more stringent) MPG target. However, mass reduction that maintains a vehicle's footprint does not create an additional MPG burden as downsizing and is a viable compliance mechanism. Several technologies, such as substitution of light, high-strength materials for conventional materials during vehicle redesigns, have the potential to reduce weight and conserve fuel while maintaining a vehicle's footprint.

NHTSA considers the likely effect of mass reduction on safety. The relationship between a vehicle's mass, size, and fatality risk is complex, and it varies in different types of crashes. As summarized above, NHTSA, along with others, have been examining this relationship for decades. The safety chapter of NHTSA's April 2012 final regulatory impact analysis (FRIA) of CAFE standards for model years 2017-2021 passenger cars and light trucks included a statistical analysis of relationships between fatality risk, mass, and footprint in model year 2000-2007 passenger car, light truck, and LTVs, based on calendar years 2002-2008 crash and vehicle-registration data; this analysis was also detailed in the 2012 Kahane report. The principal findings and conclusions of the 2012 Kahane report were mass reduction in the lighter cars, even while holding footprint constant, would significantly increase fatality risk, whereas mass reduction in the heavier LTVs would reduce societal fatality risk by reducing the fatality risk of occupants of lighter vehicles colliding with those heavier LTVs. NHTSA concluded, as a result, any reasonable combination of mass reductions that held footprint constant in model year 2017-2021 vehicles – concentrated, at least to some extent, in the heavier LTVs and limited in the lighter cars – would likely be approximately safety-neutral; it would not significantly increase fatalities and might well decrease them.

NHTSA released a preliminary report (2016 Puckett and Kindelberger report) on the relationship between fatality risk, mass, and footprint in June 2016 in advance of the Draft TAR. The preliminary report covered the same scope as the 2012 Kahane report, offering a detailed description of the databases, modeling approach, and analytical results on relationships among vehicle size, mass, and fatalities that informed the Draft TAR. Results in the Draft TAR and the 2016 Puckett and Kindelberger report are consistent with results in the 2012 Kahane report with respect to mass disparity; chiefly, societal effects of mass reduction are small, and mass reduction concentrated in larger vehicles is likely to have a beneficial effect on fatalities, while mass reduction concentrated in smaller vehicles is likely to have a detrimental effect on fatalities. There are differences between the studies in how a proportional reduction of mass would be expected to affect societal fatalities directionally, but the estimated effects are functionally near zero in both cases.

For the 2016 Puckett and Kindelberger report and Draft TAR, NHTSA, working closely with EPA and the DOE, performed an updated statistical analysis of relationships between fatality rates, mass and footprint, updating the crash and exposure databases to the latest available model years. NHTSA analyzed updated databases that included model years 2003-2010 vehicles in CY 2005- 2011 crashes. For this regulatory analysis, databases are the most up-to-date possible (model year 2004- 2011 vehicles in calendar years 2006-2012), given the processing time for crash data and the need for enough crash cases to permit statistically meaningful analyses. As in previous analyses, NHTSA has made the new databases available to the public at http://www.nhtsa.gov/fuel-economy, enabling other researchers to analyze the same data and hopefully minimizing discrepancies in results that would have occurred because of inconsistencies across databases.

7.3.3. Analysis Supporting this Final Rule

The basic analytical method used to analyze the impacts of weight reduction on safety for the final rule is the same as in the 2016 Puckett and Kindelberger report. NHTSA released the 2016 Puckett and Kindelberger report on the relationship between fatality risk, mass, and footprint in June 2016 in advance of the Draft TAR. The 2016 Puckett and Kindelberger report covered the same scope as previous NHTSA reports, offering a detailed description of the crash and exposure databases, modeling approach, and analytical results on relationships among vehicle size, mass, and fatalities that informed the Draft TAR. The modeling approach described in the 2016 Puckett and Kindelberger report was developed with the collaborative input of NHTSA, EPA, and DOE, and subject to extensive public review, scrutiny in two NHTSA-sponsored workshops, and a thorough peer review that compared it with the methodologies used in other studies.

In computing the impact of changes in mass on safety, NHTSA is faced with competing challenges. Research has consistently shown that mass reduction affects "lighter" and "heavier" vehicles differently across crash types. The 2016 Puckett and Kindelberger report found mass reduction concentrated amongst the heaviest vehicles is likely to have a beneficial effect on overall societal fatalities, while mass reduction concentrated among the lightest vehicles is likely to have a detrimental effect on fatalities. To accurately capture the differing effect on lighter and heavier vehicles, NHTSA must split vehicles into lighter and heavier vehicle classifications in the analysis. However, this poses a challenge of creating statistically meaningful results. There is limited relevant crash data to use for the analysis. Each partition of the data reduces the number of observations per vehicle classification and crash type, and thus reduces the statistical robustness of the results. The methodology employed by NHTSA was designed to balance these competing forces as an optimal trade-off to accurately capture the impact of mass-reduction across vehicle curb weights and crash types while preserving the potential to identify robust estimates.

For this final rule, as in the 2022 CAFE rule, NHTSA employed the modeling technique developed in the 2016 Puckett and Kindelberger report to analyze the updated crash and exposure data by examining the cross sections of the societal fatality rate per billion vehicle miles of travel (VMT) by mass and footprint, while controlling for driver age, gender, and other factors, in separate logistic regressions for five vehicle groups and nine crash types. NHTSA utilized the relationships between weight and safety from this analysis, expressed as percentage increases in fatalities per 100-pound weight reduction, to examine the weight impacts applied in this CAFE analysis. The effects of mass reduction on safety were estimated relative to (incremental to) the regulatory baseline in the CAFE analysis, across all vehicles for model year 2027 through model year 2050.

As in the 2012 Kahane report, 2016 Puckett and Kindelberger report, the Draft TAR, and the 2020 and 2022 CAFE rules, the vehicles are grouped into three classes: passenger cars (including both two- door and four-door cars); CUVs and minivans; and truck-based LTVs. The curb weight of passenger cars is formulated, as in the 2012 Kahane report, 2016 Puckett and Kindelberger report, Draft TAR, and 2020 CAFE rule, as a two-piece linear variable to estimate one effect of mass reduction in the lighter cars and another effect in the heavier cars. Although the analytical model has not changed for this analysis, we extend the scope of vehicles to which model outputs are applied by assuming that the incremental effect of changes in vehicle mass are the same for HDPUVs as for the heaviest LTVs. Due to sample size constraints, we chose to maintain the existing model and assume equivalent effects for heavier LTVs and HDPUVs rather than estimate separate effects. The model does include some vehicles with curb weights in common with HDPUVs (e.g., heavier Ford F-150s/Chevrolet Silverados/RAMs, Chevrolet Suburban XLs), which offers some representation of HDPUVs within the estimation of model coefficients. To gauge the impact of this assumption, we evaluate an alternative assumption of no incremental effect of HDPUV mass on safety within the sensitivity analysis.

For the previous rulemaking, NHTSA explored alternative model specifications and presented them for public comment. Among the alternatives, one specification centered on aligning passenger cars with the rest of the sample by including cars that are equipped with AWD. In previous analyses, passenger cars with AWD were excluded from the analysis because they represented a sufficiently low share of the vehicle fleet that statistical relationships between AWD status and societal fatality risk were highly prone to being conflated with other factors associated with AWD status (e.g., location, luxury vehicle status). However, the share of AWD passenger cars in the fleet has grown.

Approximately one-quarter of the passenger cars in the database have AWD, compared to an approximately five-percent share in the model year 2000-2007 database. Furthermore, all other vehicle types in the analysis include AWD as an explanatory variable. After considering the model results further, NHTSA found the inclusion of a considerable portion of the real-world fleet (i.e., passenger cars with AWD) to offer a substantial improvement to the model and has adopted this approach for the final rule.

The boundary between "lighter" and "heavier" cars is 3,201 pounds (which is the median mass of model years 2004-2011 cars in fatal crashes in calendar years 2006-2012, up from 3,106 pounds for model years 2000-

2007 cars in calendar years 2002-2008 in the 2012 NHTSA safety database, and up from 3,197 pounds for model years 2003-2010 cars in calendar years 2005-2011 in the 2016 NHTSA safety database). Likewise, for truck-based LTVs, curb weight is a two-piece linear variable with the boundary at 5,014 pounds (again, the model years 2004-2011 median, higher than the median of 4,594 pounds for model years 2000-2007 LTVs in calendar years 2002-2008 and the median of 4,947 pounds for model years 2003-2010 LTVs in calendar years 2005- 2011). CUVs and minivans are grouped together in a single group covering all curb weights of those vehicles; as a result, curb weight is formulated as a simple linear variable for CUVs and minivans. Historically, CUVs and minivans have accounted for a relatively small share of new- vehicle sales over the range of the data, resulting in less crash data available than for cars or truck-based LTVs. CUVs have increased their share of the fleet both across the years covered in the database and since, in turn increasing the importance of relationships between mass and societal fatality risk for CUVs. As the share of CUVs increases, any estimated beneficial mass reduction in CUVs will have a larger beneficial effect on overall societal fatality risk. As discussed in the sensitivity analysis below, NHTSA evaluated whether the current database contains sufficient observations of CUVs and minivans to separate these vehicles into two weight classes. The evidence does not support such a change under the current database; however, adding new calendar years and model years to the next database may yield sufficient observations to make this change. In sum, vehicles are distributed into five groups by class and curb weights: PCs < 3,201 pounds; passenger cars 3,201 pounds or greater; truck- based LTVs < 5,014 pounds; truck-based LTVs 5,014 pounds or greater; and all CUVs and minivans.

There are nine types of crashes specified in the analysis for each vehicle group: three types of single-vehicle crashes, five types of two-vehicle crashes; and one classification of all other crashes. Single-vehicle crashes include first-event rollovers, collisions with fixed objects, and collisions with pedestrians, bicycles, and motorcycles. Two-vehicle crashes include collisions with: heavy-duty vehicles; cars, CUVs, or minivans < 3,187 pounds (the median curb weight of other, non-case, cars, CUVs and minivans in fatal crashes in the database); cars, CUVs, or minivans ≥ 3,187 pounds; truck-based LTVs < 4,360 pounds (the median curb weight of other truck-based LTVs in fatal crashes in the database); and truck-based LTVs ≥ 4,360 pounds.

Grouping partner-vehicle CUVs and minivans with cars rather than LTVs is more appropriate because their front-end profile and rigidity more closely resemble a car than a typical truck-based LTV. An additional crash type includes all other fatal crash types (e.g., collisions involving more than two vehicles, animals, or trains). Splitting the vehicles from this crash type involved in crashes involving two vehicles from a lighter and a heavier group permits more accurate analyses of the mass effect in collisions of two vehicles.

For a given vehicle class and weight range (if applicable), regression coefficients for mass (while holding footprint constant) in the nine types of crashes are averaged, weighted by the number of baseline fatalities that would have occurred for the subgroup model year 2008-2011 vehicles in calendar years 2008-2012 if these vehicles had all been equipped with ESC. The adjustment for ESC, a feature of the analysis added in 2012, accounts for the fact that all mass reduction in future vehicles will apply to vehicles that are equipped with ESC, as required by NHTSA's regulations.

Table 7-26 presents the estimated percent increase in U.S. societal fatality risk per ten billion VMT for each 100-pound reduction in vehicle mass, while holding footprint constant, for each of the five vehicle classes.

Table 7-26: Fatality Increase (%) per 100-Pound Mass Reduction While Holding Footprint Constant - MY 2004-2011, CY 2006-2012

Vehicle Class	Point Estimate	95% Confidence Bounds
Cars < 3,201 pounds	1.12	-.57 to +2.81
Cars > 3,201 pounds	0.89	-.09 to +1.87
CUVs and minivans	-0.25	-1.55 to +1.04
Truck-based LTVs < 5,014 pounds	0.31	-.51 to +1.13

Truck-based LTVs > 5,014 pounds*	-0.61	-1.46 to +.25

*-The point estimate for this group is also applied to HDPUVs.

Techniques developed in the 2011 (preliminary) and 2012 (final) Kahane reports have been retained to test statistical significance and to estimate 95 percent confidence bounds (sampling error) for mass effects and to estimate the combined annual effect of removing 100 pounds of mass from every vehicle (or of removing different amounts of mass from the various classes of vehicles), while holding footprint constant. Confidence bounds estimate only the sampling error internal to the data used in the specific analysis that generated the point estimate. Point estimates are also sensitive to the modification of components of the analysis, as discussed at the end of this subchapter. However, this degree of uncertainty is methodological in nature rather than statistical.

None of the estimated effects have 95-percent confidence bounds that exclude zero, and thus are not statistically significant at the 95-percent confidence level. NHTSA has evaluated these results and provided them for the purposes of transparency. Sensitivity analyses have confirmed that the exclusion of these statistically insignificant results would not affect our policy determination, because the net effects of mass reduction on safety costs are small relative to predominant estimated benefit and cost impacts. Among the estimated effects, the most important effects of mass reduction are, as expected, concentrated among the lightest and heaviest vehicles. Societal fatality risk is estimated to: (1) increase by 1.12 percent if mass is reduced by 100 pounds in the lighter cars; and (2) decrease by 0.61 percent if mass is reduced by 100 pounds in the heavier truck-based LTVs.

A key constraint limiting statistical significance is that the analysis focuses on societal fatality risk (i.e., all fatalities, including crash partners and people outside of vehicles, such as pedestrians, cyclists, and motorcyclists) rather than merely in-vehicle fatality risk, which yields estimates that are smaller in magnitude (and thus more difficult to identify meaningful differences from zero) than estimates representing changes in in-vehicle fatality risk. That is, compared to an analysis of in-vehicle fatality risk (which would tend to yield relatively large estimated effects of mass reduction – either relatively highly-beneficial to reduce mass in the heaviest vehicles, or relatively highly-detrimental to reduce mass in the lightest vehicles), the focus on societal fatalities tends to yield relatively small (net) effects of mass reduction on fatality risk. This arises because the effects of mass reduction inherently net out to some extent in two-vehicle crashes: Impacts of mass reduction that protect one set of occupants (i.e., occupants of the vehicle striking or being struck by the vehicle that has experienced mass reduction) are accompanied by impacts that make the other set of occupants more vulnerable (i.e., occupants of the vehicle that has experienced mass reduction).

NHTSA judges the central value estimates are the best estimates available; the estimates offer a stronger statistical representation of relationships among vehicle curb weight, footprint, and fatality risk than an assumption of no correlation whatsoever. NHTSA appropriately presents the statistical uncertainty. For example, the central values for the highest vehicle weight group (LTVs 5,014 pounds or heavier) and the lowest vehicle weight group (passenger cars lighter than 3,201 pounds) (which, based on fundamental physics, are expected to have the greatest impact of mass reduction on safety) are economically meaningful,[1121] and are in line with the prior analyses used in past NHTSA CAFE rulemakings. As shown in Table 7-26, the estimated coefficients have trended to lower numerical values in successive studies, but remain positive for lighter cars and negative for heavier LTVs.

The regression results are constructed to project the effect of changes in mass, independent of all other factors, including footprint. With each additional change from the current environment (e.g., the scale of mass change, presence and prevalence of safety features, demographic characteristics), the results may become less representative. That is, although safety features and demographic factors are accounted for separately,

[1121] NHTSA uses "economically meaningful results" to mean values that have an important, practical implication, but may be derived from estimates that do not meet traditional levels of statistical significance. For example, if the projected economic benefit of a project equaled $100 billion, the agency would consider the impact economically meaningful, even if the estimates used to derive the impact were not statistically significant at the 95-percent confidence level. Conversely, if the projected economic benefit of a project equaled $1, the agency would not consider the impact economically meaningful, even if the estimates used to derive the impact were statistically significant at the 99.99-percent confidence level. In the case above, the results associated with the lightest and heaviest vehicle types were considered to be economically meaningful because the associated safety costs were large, and the estimates had magnitudes meaningfully different from zero and were statistically significant at the 85- percent confidence level.

the estimated effects of mass are identified under the specific mix of vehicles and drivers in the data. NHTSA notes that the analysis accounts for safety features that are optional but available across all model years in the sample (most notably electronic stability control, which was not yet mandatory for all model years in the sample) and calibrates historical safety data to account for future fleets with full ESC penetration to reflect the mandate.

NHTSA considered the near multicollinearity of mass and footprint to be a major issue in the 2010 Kahane report and voiced concern about inaccurately estimated regression coefficients. High correlations between mass and footprint and variance inflation factors have not changed from model year 1991-1999 to model year 2004-2011; large vehicles continued to be, on average, heavier than small vehicles to the same extent as in the previous decade.

Nevertheless, multicollinearity appears to have become less of a problem in the 2012 Kahane, 2016 Puckett and Kindelberger/Draft TAR, and 2020 and 2021 CAFE rulemaking analyses. Ultimately, only 4 of the 27 core models of fatality risk by vehicle type in the 2021 analysis indicate the potential presence of effects of multicollinearity, with estimated effects of mass and footprint reduction greater than two percent per 100-pound mass reduction and one-square-foot footprint reduction, respectively; these three models include passenger cars and CUVs in first-event rollovers, and CUVs in collisions with LTVs greater than 4,360 pounds. This result is consistent with the 2016 Puckett and Kindelberger report, which found only three cases out of 27 models with estimated effects of mass and footprint reduction greater than two percent per 100-pound mass reduction and one-square-foot footprint reduction.

Revising the approach to account for AWD status for passenger cars adds an additional model for which the estimated effects of mass reduction indicate the potential presence of the effects of multicollinearity: crashes with heavy vehicles. Single estimated coefficients for one of lighter and heavier passenger cars are also consistent with potential effects of multicollinearity for the models of crashes with heavier LTVs (for heavier passenger cars) and all other crashes (for lighter passenger cars). Because the only change between the 2022 analysis and this analysis is the inclusion of AWD as an explanatory variable for passenger cars, changes in individual estimated coefficients and their statistical significance represent shifts associated with changes in the set of explanatory variables rather than any change in correlations among our focal variables of interest.

Multicollinearity is one of the important concerns regarding the robustness of the results, along with estimated statistical significance. An alternative gauge of the robustness of the results is stability in estimates over time. That is, concerns regarding limitations of the data and low levels of statistical significance may be dampened if related, but substantially different analyses using the same methodology yield consistent results. Table 7-27 compares the fatality coefficients from the 2012 Kahane report (model year 2000-2007 vehicles in calendar years 2002-2008) and the 2016 Puckett and Kindelberger report and Draft TAR (model year 2003-2010 vehicles in calendar years 2005-2011).

Table 7-27: Fatality Increase (%) per 100-Pound Mass Reduction While Holding Footprint Constant (2012-2016 Analyses)

Vehicle Class[1122]	2012 Report Point Estimate	2016 Report/Draft TAR Point Estimate	2012 Report 95% Confidence Bounds	2016 Report 95% Confidence Bounds
Lighter Passenger Cars	1.56	1.49	+.39 to +2.73	-.30 to +3.27
Heavier Passenger Cars	.51	.50	-.59 to 1.60	-.59 to +1.60
CUVs and Minivans	-.37	-.99	-1.55 to +.81	-2.17 to +.19
Lighter Truck-Based LTVs	.52	-.10	-.45 to +1.48	-1.08 to +.88

[1122] Median curb weights in the 2012 Kahane report - 3,106 pounds for cars, 4,594 pounds for truck-based LTVs. Median curb weights in the 2016 Puckett and Kindelberger report - 3,197 pounds for cars, 4,947 pounds for truck-based LTVs.

Heavier Truck-Based LTVs	-.34	-.72	-.97 to + .30	-1.45 to +.02

The most recent results are directionally the same as in 2012; in the 2016 analysis, the estimate for lighter LTVs was of opposite sign (but small magnitude). Consistent with the 2012 Kahane and 2016 Puckett and Kindelberger reports, mass reductions in lighter cars are estimated to lead to increases in fatalities, and mass reductions in heavier LTVs are estimated to lead to decreases in fatalities.

The estimated mass effect for heavier truck-based LTVs has higher statistical significance in this analysis and in the 2016 Puckett and Kindelberger report than in the 2012 Kahane report; both estimates are statistically significant at the 85-percent confidence level, unlike the corresponding estimate in the 2012 Kahane report. The estimated mass effect for lighter truck-based LTVs is insignificant and positive in this analysis and the 2012 Kahane report, while the corresponding estimate in the 2016 Puckett and Kindelberger report was insignificant and negative.

NHTSA believes the most recent analysis represents the best estimate of the impacts of mass reduction that results in changes in mass disparities on crash fatalities, although it is important to note that these best estimates are not significantly different from zero. We have conducted sensitivity analyses to illustrate the uncertainty of the estimates, and we have determined that inclusion of these estimates does not alter the agency's determination of what is maximum feasible because the effects are so small. We continue to believe that is reasonable for the analysis to continue to include the best available estimates despite their lack of statistical significance at the 0.05 level. Similar to past analyses, the most recent analysis uses the best available data and estimates. NHTSA feels it is inappropriate to ignore likely impacts of the standards simply because the best available estimates have confidence levels below 95 percent; uniform estimates of zero are statistically weaker than the estimates identified in the analysis, and thus are not the best available. Because the point estimates are derived from the best-fitting estimates for each crash type (all of which are non-zero), the confidence bounds around an overall estimate of zero would necessarily be larger than the corresponding confidence bounds around the point estimates presented here. Ultimately, the point estimates for the lightest and heaviest vehicles in the sample are the estimates that have shown consistent directionality (and, to a lesser extent, magnitude) across studies, and these estimates are the most important in representing the effects of changes in mass disparity consistent with theory on the role of mass disparity in societal fatality risk. Thus, the point estimates for lighter passenger cars and heavier LTVs offer the highest informative value among the estimates in the analysis; the smaller estimates corresponding to vehicles near the median of the fleet curb weight distribution are likely to be less informative.

The sensitivity analysis in the accompanying FRIA Chapter 9 "Expanded Sensitivity Analysis" provides an evaluation of extreme cases in which all the estimated net fatality rate impacts of mass reduction are either at their fifth- or 95th-percentile values. The range of net impacts in the sensitivity analysis not only covers the relatively more likely case that uncertain, yet generally offsetting, effects are distinct from the central estimates considered here (e.g., in a plausible case where mass reduction in the heaviest LTVs is less beneficial than indicated by the central estimates, it would also be relatively likely that mass reduction in the lightest passenger cars would be less harmful, yielding a similar net impact), but also covers the relatively unlikely case that all of the estimates are uncertain in the same direction.

The 2012 Kahane report, the 2016 Puckett and Kindelberger, the Draft TAR, and the 2020 and 2022 CAFE rules all have shown that both mass disparity and vehicle size impact societal safety. Across recent rulemakings, the analyses have confirmed a protective effect of vehicle size (i.e., societal fatality risk decreases as footprint increases). As mentioned previously, NHTSA believes vehicle footprint-based standards create no incentive for vehicle manufacturers to downsize or upsize their vehicles. In turn, we assume changes in standards will not impact vehicle size and size-related safety impacts. On the other hand, mass reduction is a cost-effective technology for increasing fuel economy. Therefore, NHTSA includes the assessment of safety impacts related to mass reduction and its potential impact on mass disparity. In this regard, the CAFE Model estimates of how mass reductions will be distributed across the new vehicle fleet and the effects of electrification which tends to increase vehicle mass, can strongly affect conclusions about the effects of standards on safety. As discussed throughout this mass-safety subchapter, comprehensive consideration of the various studies and workshops on the impact of vehicle mass disparity on safety is presented and conclude there has been a relationship historically. The fleet simulation study, discussed in the next subchapters, further supports the existence of this relationship and that this relationship will continue to exist in future vehicle designs. However, in the analysis presented here, the relationship between mass and safety was not estimated to be significantly different from zero at the 0.05 level relationship and that this relationship will continue to exist in future vehicle designs.

Vehicle mass continued an historical upward trend across the model years in the databases. The average (VMT-weighted) masses of passenger cars and CUVs both increased by approximately 3% from model year 2004 to model year 2011 (3,184 pounds to 3,289 pounds for passenger cars, and 3,821 pounds to 3,924 pounds for CUVs). Over the same period, the average mass of minivans increased by 6% (from 4,204 pounds to 4,462 pounds), and the average mass of LTVs increased by 10% (from 4,819 pounds to 5,311 pounds). Historical reasons for mass increases within vehicle classes include - manufacturers discontinuing lighter models; manufacturers re-designing models to be heavier and larger; and shifting consumer preferences with respect to cabin size and overall vehicle size. Indeed, not only have vehicles increased in mass, but also footprint. Across vehicles involved in fatal accidents in the analysis, mean footprint increased by between approximately 3% (for CUVs) and 8% (for sedans). The principal difference between heavier vehicles, especially truck-based LTVs, and lighter vehicles, especially passenger cars, is mass reduction has a different effect in collisions with another car or LTV. When two vehicles of unequal mass collide, the change in velocity (delta-v) is greater in the lighter vehicle. Through conservation of momentum, the degree to which the delta-v in the lighter vehicle is greater than in the heavier vehicle is proportional to the ratio of mass in the heavier vehicle to mass in the lighter vehicle.

The relationships among vehicle velocities and vehicle masses in inelastic collisions are given in Equation 7-1.

Equation 7-1: Final Velocity for Focal Vehicle in an Inelastic Collision

$$v_{1f}=\frac{C_R m_2(v_{2i}-v_{1i}) + m_1 v_{1i} + m_2 v_{2i}}{m_1+m_2}$$

Where:

v_1 is the velocity for a focal vehicle

v_2 is the velocity for a partner vehicle

i and f represent initial and final velocities respectively

m_1 and m_2 are the masses of the vehicles

C_R is the coefficient of restitution (which represents effects extending the time of deceleration and dissipating energy through deformation and heat transfer).

As the final velocity decreases, delta-v increases[1123]. Thus, delta-v increases with the mass of the partner vehicle but is unchanged if both vehicles increase their mass proportionally.

Because fatality risk is a positive function of delta-v, the fatality risk in the lighter vehicle in two-vehicle collisions is also higher. Vehicle design can reduce the magnitude of delta-v to some degree (e.g., changing the stiffness of a vehicle's structure could dampen delta-v for both crash partners). These considerations drive the overall result: increased mass disparity is associated with an increase in fatality risk in lighter cars, a decrease in fatality risk in heavier LTVs, CUVs, and minivans, and has smaller effects in the intermediate groups. Mass reduction may also be harmful in a crash with a movable object such as a small tree, which may break if hit by a high mass vehicle resulting in a lower delta-v than may occur if hit by a lower mass vehicle which does not break the tree and therefore has a higher delta-v. However, in some types of crashes not involving collisions between cars and LTVs, especially first-event rollovers and impacts with fixed objects

[1123] Delta-v refers to the change in velocity experienced during a crash.

or collisions with vulnerable road users (e.g., pedestrians and cyclists), mass reduction may not be harmful and may even be beneficial.

Ultimately, delta-v is a direct function of relative vehicle mass for given vehicle structures. Removing some mass from the heavier vehicle involved in an accident with a lighter vehicle reduces the delta-v in the lighter vehicle, where fatality risk is higher, resulting in a large benefit to the passengers of the lighter vehicle. This is partially offset by a small increase in the delta-v in the heavy vehicle; however, the fatality risk is lower in the heavier vehicle and remains relatively low despite the increase in delta-v. In sum, the change in mass and delta-v from mass reduction in heavier vehicles results in a net societal benefit.

These considerations drive the overall result that has been observed historically: Mass reduction in lighter cars is associated with an increase in societal fatality risk; mass reduction in heavier LTVs, CUVs, and minivans is associated with a decrease in societal fatality risk; and mass reduction in the intermediate groups has smaller effects. These results can be considered in concert to represent the potential effects of fleetwide mass reduction; in particular, certain ratios of mass reduction across the fleet may have little to no net effect on societal fatalities.

Mass reduction may also be harmful in a crash with a movable object such as a small tree, which may break if hit by a high mass vehicle resulting in a lower delta-v than may occur if hit by a lower mass vehicle which does not break the tree and therefore has a higher delta-v. However, in some types of crashes not involving collisions between cars and LTVs, especially first-event rollovers and impacts with fixed objects, mass reduction may not be harmful and may be beneficial. To the extent lighter vehicles may respond more quickly to braking and steering or may be more stable because their center of gravity is lower, they may more successfully avoid crashes or reduce the severity of crashes.

Farmer, Green, and Lie, who reviewed the 2010 Kahane report, again peer-reviewed the 2011 Kahane report. In preparing his 2012 report (along with the 2016 Puckett and Kindelberger report and Draft TAR), Kahane also took into account Wenzel's assessment of the preliminary report and its peer reviews, DRI's analyses published early in 2012, and public comments such as the International Council on Clean Transportation's comments submitted on NHTSA and EPA's 2010 notice of joint rulemaking. These comments prompted supplementary analyses, especially sensitivity tests, discussed at the end of this subchapter.

The regression results are best suited to predict the effect of a small change in mass, leaving all other factors, including footprint, the same. With each additional change from the current environment (e.g., the scale of mass change, presence and prevalence of safety features, demographic characteristics), uncertainty in the model results may increase. It is recognized that the light-duty vehicle fleet in the model year 2027-2031 timeframe will be different from the model year 2004-2011 fleet analyzed here.

Nevertheless, one consideration provides some basis for confidence in applying regression results to estimate effects of relatively large mass reductions or mass reductions over longer periods. The central results represent the findings from NHTSA's sixth evaluation of effects of mass reduction and/or downsizing, comprising databases ranging from model year 1985 to model year 2011.

Results of the six studies are not identical, but they have been consistent to a point. During this time period, many vehicle makes and models have increased substantially in mass, sometimes as much as 30-40%. If the statistical analysis has, over the past years, been able to accommodate mass increases of this magnitude, perhaps it will also succeed in modeling effects of mass reductions of approximately 10-20%, should they occur in the future.

7.3.4. Alternative Mass Safety Model Specifications Examined

Table 7-28 shows the principal findings and includes sampling-error confidence bounds for the five parameters used in the CAFE Model. The confidence bounds represent the statistical uncertainty that is a consequence of having less than a census of data. NHTSA's 2011, 2012, and 2016 reports acknowledged another source of uncertainty – The mass-safety baseline statistical model can be varied by choosing different control variables or redefining the vehicle classes or crash types, which for example, could produce different point estimates.

Beginning with the 2012 Kahane report, NHTSA has provided results of 11 plausible alternative models. Each alternative model was tested or proposed by: Farmer (IIHS) or Green (UMTRI) in their peer reviews; Van Auken (DRI) in his public comments; or Wenzel in his parallel research for DOE. The 2012 Kahane and 2016 Puckett and Kindelberger reports provide further discussion of the models and the rationales behind them.

Alternative models use NHTSA's databases and regression-analysis approach but differ from the CAFE Model's approach in one or more explanatory variables, assumptions, or data restrictions. NHTSA applied the 11 techniques to the latest databases to generate alternative CAFE Model coefficients. The range of estimates produced by the alternative models offer insight to the uncertainty inherent in the formulation of the model, subject to the caveat these 11 tests are, of course, not an exhaustive list of conceivable alternatives.

The central and alternative results follow, ordered from the lowest to the highest estimated increase in societal risk per 100-pound reduction for cars weighing less than 3,201 pounds.

Table 7-28: Fatality Increase (%) Per 100-Pound Mass Reduction While Holding Footprint* Constant (Alternative Models)

		Cars < 3,201 Pounds	Cars ≥ 3,201 Pounds	CUVs & Minivans	LTVs† < 5,014 Pounds	LTVs† ≥ 5,014 Pounds
Baseline Estimate		1.1220	0.4289	-0.25	0.31	-0.61
95% Confidence Bounds (sampling error)	Lower:	-0.5735	-0.0967	-1.55	-0.51	-1.46
	Upper:	2.8175	1.875	1.04	1.13	0.25
11 Alternative Models:						
1. Without CY control variables		-0.2618	-0.507	-0.58	0.35	-0.24
2. By track width & wheelbase		0.696	0.9154	-0.48	-0.44	-0.90
3. Track width/wheelbase w. stopped veh data		0.763	-0.3802	-0.18	-0.77	-1.91
4. Without non-significant control variables		0.908	0.267	0.14	0.36	-0.50
5. CUVs/minivans weighted by 2010 sales		1.20	0.42	-0.06	0.31	-0.61
6. With stopped-vehicle State data		1.2432	-0.217	-0.08	0.21	-1.55
6. CUVs/minivans weighted by 2010 sales		1.20	0.42	-0.06	0.31	-0.61
7. Including muscle/police/AWD cars/big vans		1.56	1.01	-0.25	0.87	0.43
8. Limited to drivers with BAC=0		1.723	1.3376	0.01	0.35	-0.74
9. Control for vehicle manufacturer		2.089	1.8851	-0.01	1.12	0.30

10. Limited to good drivers‡	2.215	2.241.80	-0.33	0.40	-0.45
11. Control for vehicle manufacturer/nameplate	2.226	2.9670	-0.55	1.13	0.50

*While holding track width and wheelbase constant (rather than footprint) in alternative model nos. 2 and 3.

†Excluding CUVs and minivans. Estimate would also be applied to HDPUVs in the CAFE Model.

‡ Blood alcohol concentration (BAC) =0, no drugs, valid license, at most 1 crash and 1 violation during the past 3 years.

For example, in cars weighing less than 3,201 pounds, the baseline estimate associates 100- pound mass reduction, while holding footprint constant, with a 1.1256 percent increase in societal fatality risk. The corresponding estimates for the 11 alternative models range from a 0.18 percent 26 to a 2.226 percent increase.

The alternative models tested illustrate both the fragility and the robustness of baseline estimates. On the one hand, the variation among NHTSA's coefficients is quite large relative to the baseline estimate - In the preceding example of cars < 3,201 pounds, the estimated coefficients range from almost zero to almost approximately double the baseline estimate. This result underscores the key relationship that the societal effect of mass reduction is small, a finding shared by Wenzel (2011, 2018). In other words, varying how to model some of these other vehicle, driver, and crash factors, can appreciably change the estimate of the societal effect of mass reduction.

On the other hand, variations are not particularly large in absolute terms. The ranges of alternative estimates are generally in line with the sampling-error confidence bounds for the central estimates. Generally, in alternative models as in the CAFE Model, mass reduction tends to be relatively more harmful in the lighter vehicles and more beneficial in the heavier vehicles, just as they are in the central analysis. In all models, the point estimate of the coefficient is positive for the lightest vehicle class, cars < 3,201 pounds. In 10 out of 11 models, the point estimate is negative for CUVs and minivans, and in nine out of 11 models the point estimate is negative for LTVs ≥ 5,014 pounds. NHTSA believes the CAFE Model case uses the most rigorous methodology, as discussed further above, and provides the best estimates of the impacts of differential mass reductions on safety. As discussed in the preceding section, it is important to note that none of the mass-related safety coefficients applied in the CAFE Model are statistically significant distinguishable from zero at the 95-percent confidence level.

7.3.5. Non-fatal Mass/Size Safety Impacts

Research into the effect of changes in mass on safety has typically been confined to fatality impacts, but logically, the same physics that increase or decrease fatality risk should impact injury and property damage risk in a directionally consistent manner. For non-fatal crash impacts, we assume that the rates of non- fatal injuries and property damage to vehicles projected by our models will change in the same proportion to changes in vehicles' mass disparities as do those vehicles' fatality rates. This produces estimates of changes in incidence for nonfatal injuries and PDO vehicles due to mass changes in the new vehicle fleet for each model year.

7.3.6. Fleet Simulations Model

Commenters to recent CAFE rulemakings, including some vehicle manufacturers, have suggested that designs and materials of more recent model year vehicles may have weakened the historical statistical relationships between mass, size, and safety. NHTSA agreed that the statistical analysis would be improved by using an updated crash and exposure database reflecting more recent safety technologies, vehicle designs and materials, and reflecting changes in the vehicle fleet. As mentioned above, a new crash and exposure database was created with the intention of capturing modern vehicle engineering and has been employed for assessing safety effects for CAFE rules since 2012.

NHTSA has traditionally relied solely on real-world crash data as the basis for projecting the future safety implications for regulatory changes. NHTSA is required to consider relevant data in setting standards. Every fleet regulated by NHTSA's standards differs from the fleet used to establish said standard, and as such, the light-duty and HDPUV vehicle fleet in the model year 2027-2032 timeframe will be different from the model year 2004-2011 fleet analyzed in the 2012 study. This is not a new or unique phenomenon, but instead is an inherent challenge in regulating an industry reliant on continual innovation. The statistical analysis reviewed above is NHTSA's sixth evaluation of effects of mass reduction and/or downsizing, comprising databases ranging from model year 1985 to model year 2011. Despite continual claims that modern light-weight engineering will render current data obsolete, results of the six studies, while not identical, have been generally consistent in showing a small, negative impact related to increased mass disparity. NHTSA strongly believes that real-world crash data remain the best, most relevant data to measure the effect of mass reduction on safety.

However, because light-weight vehicle designs introduce fundamental changes to the structure of the vehicle, there remains a persistent question of whether historical safety trends will apply. To address this concern and to verify that real-world crash data remain an appropriate source of data for projecting mass-safety relationships in the future fleet, in 2014, NHTSA sponsored research to develop an approach to utilize experimental light-weight vehicle designs to evaluate safety in a broader range of real-world representative crashes. NHTSA contracted with George Washington University to develop a fleet simulation model to study the impact and relationship of light-weighted vehicle design with injuries and fatalities. The study involved simulating crashes on eight test vehicles, five of which were equipped with light-weight materials and advanced designs not yet incorporated into the U.S. fleet. The study centered on the comparison of safety performance for hypothetical light-weighted vehicle designs relative to a baseline of existing vehicles. The study assessed safety impacts of making newer vehicles lighter across frontal crash types, including crashes with fixed objects and other vehicles (both older, heavier vehicles and newer, lighter vehicles, to represent variation in crash risks as a function of mass disparity in the vehicle fleet), across a wide range of vehicle speeds, and with mid-size male and mid-size female dummies. It is worth noting, given the questions raised about whether new materials and designs have weakened or eliminated the historical relationship between mass and safety, that the model year vehicles evaluated in this study are from ten to twenty years ago, and materials and designs have continued to evolve during that time.

The methodology focused on frontal crashes because of the availability of existing vehicle and occupant restraint models. Representative crashes were simulated between baseline and light- weight vehicles against a range of vehicles and roadside objects using two different size belted driver occupants (adult male and small female) only. No passenger(s) or unbelted driver occupants were considered in this fleet simulation. The occupant injury risk from each simulation was calculated and summed to obtain combined occupant injury risk. The combined occupant injury risk was weighted according to the frequency of real-world occurrences to develop overall societal risk for baseline and light-weighted vehicles. Note - The generic restraint system developed and used in the baseline occupant simulations was also used in the light-weighted vehicle occupant simulations as the purpose of this fleet simulation was to understand changes in societal injury risks (SIRs) because of mass reduction for different classes of vehicles in frontal crashes. No modifications to the restraint systems were made for light- weighted vehicle occupant simulations. Any modifications to restraint systems to improve occupant injury risks or SIRs in the light-weighted vehicle, would have conflated results without identifying effects of mass reduction only. The following subchapters provide an overview of the fleet simulation study:

Eight vehicles were evaluated in the study. All light-weighted variants were designed for the study rather than real-market alternatives; thus, the light-weighted vehicles in the study may differ from corresponding versions that could have feasibly been produced by the original manufacturer. The vehicles included in the study:

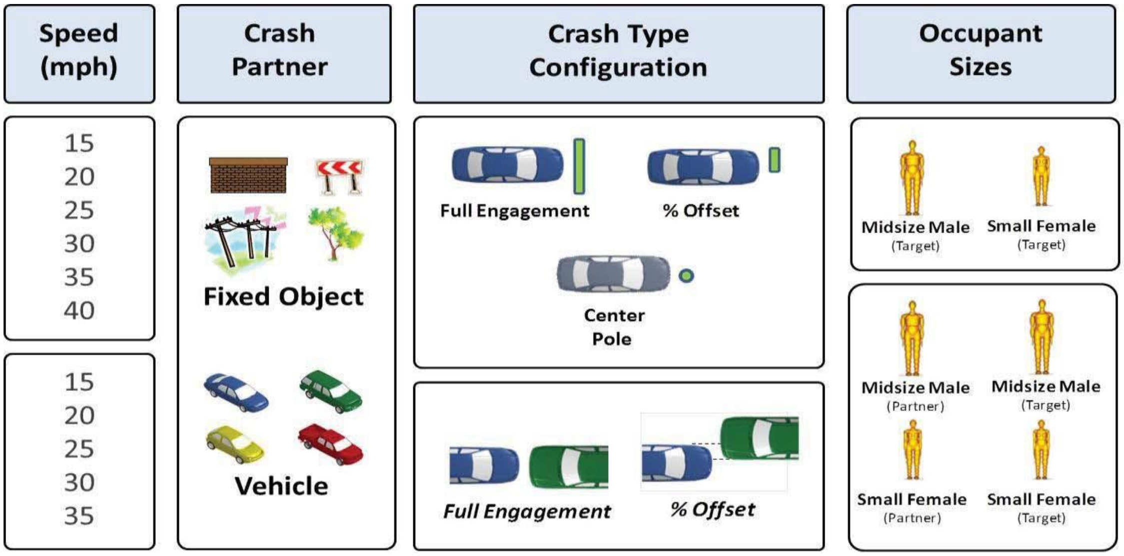
2001 model year Ford Taurus finite element model baseline and two simple design variants included a 25 percent lighter vehicle while maintaining the same vehicle front end stiffness and 25 percent overall stiffer vehicle while maintaining the same overall vehicle mass.

2011 model year Honda Accord finite element baseline vehicle and its 20 percent light- weight vehicle designed by Electricore. This mass reduction study was sponsored by NHTSA.

2009/2010 model year Toyota Venza finite element baseline vehicle and two design variants included a 20 percent light-weight vehicle model (2010 Venza) funded by EPA and International Council on Clean Transportation (ICCT) and a 35 percent light-weight vehicle (2009 Venza) funded by California Air Resources Board.

Light-weight vehicles were designed to have similar vehicle crash pulses as baseline vehicles. More than 440 vehicle crash simulations were conducted for the range of crash speeds and crash configurations to generate crash pulse and intrusion data points shown in Figure 7-5. The crash pulse data and intrusion data points will be used as inputs in the occupant simulation models.

Figure 7-5: Vehicle Crash Simulations



For vehicle-to-vehicle impact simulations, four finite element models were chosen to represent the fleet as shown in Table 7-29. The partner vehicle models were selected to represent a range of vehicle types and weights. It was assumed vehicle models would reflect the crash response for all vehicles of the same type, e.g., mid-size car. Only the safety or injury risk for the driver in the target vehicle and in the partner vehicle were evaluated in this study.

Table 7-29: Base Vehicle Models Used in the Fleet Simulation Study

Vehicle Models		FE Weight / No. Parts /Elements	
Taurus (MY 2000 – 2007)			1505 kg / 802 / 973,351
Yaris (MY 2005 – 2013)			1100 kg / 917 / 1,514,068
Explorer (MY 2002 – 2005)			2025 kg / 923 / 714,205
Silverado (MY 2007 –2013)			2270 kg / 719 / 963,482

As noted, vehicle simulations generated vehicle deformations and acceleration responses utilized to drive occupant restraint simulations and predict the risk of injury to the head, neck, chest, and lower extremities. In all, more than 1,520 occupant restraint simulations were conducted to evaluate the risk of injury for mid-size male and small female drivers.

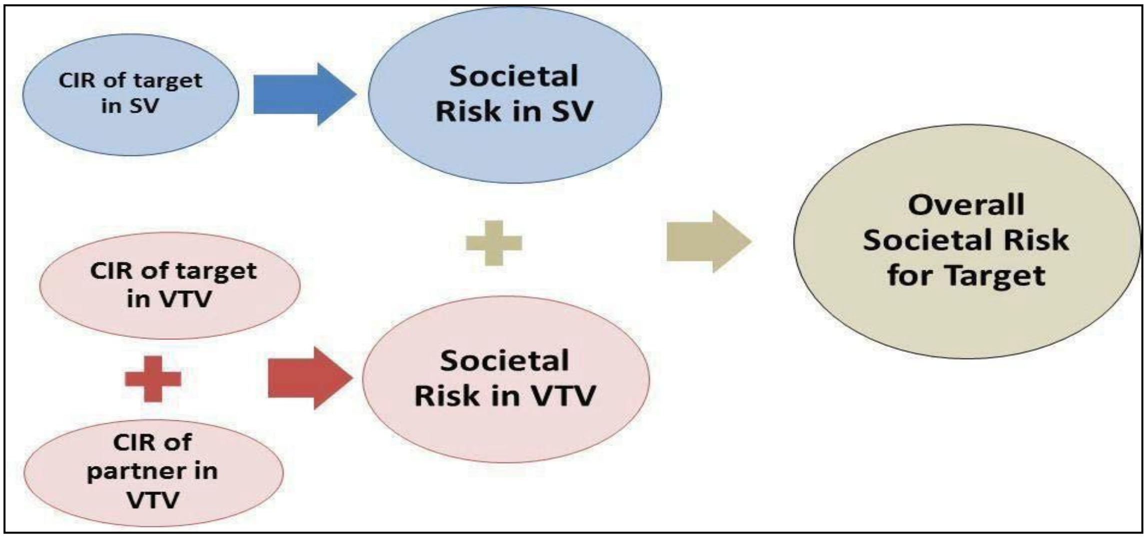
The SIR, as computed by Equation 7-2, for a target vehicle v in frontal crashes is an aggregate of individual serious crash injury risks weighted by real-world frequency of occurrence (v) of a frontal crash incident. A crash incident corresponds to a crash with different partners (Npartner) at a given impact speed (Pspeed), for a given driver occupant size (Loccsize), in the target or partner vehicle (T/P), in a given crash configuration (Mconfig), and in a single- or two-vehicle crash (Kevent). CIR (v) represents the combined injury risk (by body region) in a single crash incident. (v) designates the weighting factor, i.e., percent of occurrence, derived from National Automotive Sampling System Crashworthiness Data System (NASS CDS) for the crash incident. A driver age group of 16 to 50 years old was chosen to provide a population with a similar, i.e., more consistent, injury tolerance.

Equation 7-2: Societal Injury Risk

$$SIR_{frontal}(v) = \sum_{k=1}^{Kevent} \sum_{l=1}^{Loccsize} \sum_{m=1}^{Mconfig} \sum_{n=0}^{Npartner} \sum_{o=1}^{T/P} \sum_{p=1}^{Pspeed} w_{klmnop}(v) * CIR_{klmnop}(v)$$

Figure 7-6 shows how change in societal risk is computed.

Figure 7-6: Diagram of Computation for Overall Change in Societal Risk



The fleet simulation was performed using the best available engineering models, with base vehicle restraint and airbag settings, to estimate societal risks of future light-weight vehicles. The range of the predicted risks for the baseline vehicles is from 1.25 to 1.56 percent, with an average of 1.39 percent, for the NASS frontal crashes that were simulated. The change in driver injury risk between the baseline and light-weighted vehicles will provide insight into the estimate of modification needed in the restraint and airbag systems of light-weight vehicles. If the difference extends beyond the expected baseline vehicle restraint and airbag capability, then adjustments to the structural designs would be needed. Results from the fleet simulation study show that the trend of increased SIR for light-weighted vehicle designs, as compared to their baselines, occurs for both single vehicle and two-vehicle crashes. Results are listed in Table 7-30.

In general, the SIR in the frontal crash simulation associated with the small size driver is elevated when compared to that of the mid-size driver. However, both occupant sizes had levels of injury risk in the simulated impact configurations representative of the regulatory and consumer information testing. NHTSA examined three methods for combining injuries with different body regions. One observation was that the baseline mid-size CUV model was more sensitive to leg injuries.

Table 7-30: Overall Societal Risk Calculation Results for Model Runs, with Base Vehicle Restraint and Airbag Settings Being the Same for All Vehicles, in Frontal Crash Only

Target Vehicle	Passenger Car Baseline	Passenger Car LW	CUV Baseline	CUV Low Option	CUV High Option
Weight (lbs.)	3681	2964	3980	3313	2537
Reduction		716		668	1444
% Mass Reduction		19%		17%	36%
Societal Risk I	1.56%	1.73%	1.36%	1.46%	1.57%
Delta Increase		0.17%		0.10%	0.21%
Societal Risk II	1.43%	1.57%	1.14%	1.20%	1.30%
Delta Increase		0.14%		0.06%	0.16%
Societal Risk IIP	1.44%	1.59%			
Delta Increase		0.15%			

Societal Risk I - Target + Partner Combined AIS3+ risk of Head, Neck, Chest & Femur Societal Risk II - Target + Partner Combined AIS3+ risk of Head, Neck, and Chest

Societal Risk IIP - Target + Partner Combined AIS3+ risk of Head, Neck, and Chest with A-Pillar Intrusion Penalty

This study only looked at light-weight designs for a midsize sedan and a mid-size CUV and did not examine safety implications for heavier vehicles. The study was also limited to only frontal crash configurations and considered just mid-size CUVs whereas the statistical regression model considered all CUVs and all crash modes.

The change in the safety risk from the model year 2010 fleet simulation study was directionally consistent with results for passenger cars from the 2012 Kahane report, the 2016 Puckett and Kindelberger report, the 2020 and 2022 final rules, and the analysis used for this final rule. As noted, fleet simulations were performed only in frontal crash mode and did not consider other crash modes including rollover crashes.

This fleet simulation study does not provide information that can be used to modify coefficients derived for the final rule regression analysis because of the restricted types of crashes and vehicle designs. As explained earlier, the fleet simulation study assumed restraint equipment to be as in the baseline model, in which restraints/airbags are not redesigned to be optimal with light-weighting.

The fleet simulation study also does not provide information that can be used to modify the analysis with respect to BEVs. To address this limitation for future rulemakings, NHTSA is undertaking research into crashes between ICE vehicles and BEVs, including a simulation study. This research seeks to quantify the extent to which key BEV attributes – chiefly, increased frontal crush space, lower center of gravity, increased mass, and deformation patterns – influence crash safety outcomes for occupants of ICE vehicles and BEVs.

7.4. Impact of Vehicle Scrappage and Sales Response on Fatalities

The sales response discussed above in Chapter 4.1 impacts the number of vehicles produced in a specific model year and, consequently, in service in subsequent years. Reduced new vehicle sales cause an increase in fatalities due primarily to slower adoption of safer vehicles while increased vehicle sales would have the opposite effect. The scrappage response described in Chapter 4.2 impacts safety because it changes the rate at which older, and less-safe vehicles are retired from service. Collectively, sales and scrappage influence how quickly the fleet will “turn over” to newer vehicles, which tend to be safer than older vehicles. Any effects on fleet turnover caused by fuel economy and efficiency standards increasing the price of new and used vehicles—either from changes in the pace of vehicle retirement or sales of new vehicles—will affect the distribution of both ages and model years present in the on-road fleet. Because each of these vintages carries with it inherent rates of fatal crashes, and newer vintages are generally safer than older ones, changing that distribution of ages within the fleet will change the total number of on-road fatalities under each regulatory alternative.

The agency uses the fatality risk of vehicles combined with the changes in VMT across alternatives to calculate the safety impact of fleet turnover. The fatality risk measures the likelihood that a vehicle will be involved in a fatal accident per mile driven. As described in Chapter 7.1.7, NHTSA calculates the fatality risk of a vehicle based on the vehicle's model year, age, and style, while controlling for factors that are independent of the intrinsic nature of the vehicle, such as behavioral characteristics. Newer vehicles will have a lower fatality risk than older vehicles, all else being equal. Fleetwide safety is also anticipated to benefit from both the improvement and increased prevalence of advance crash technologies as discussed in Chapter 7.2, hence more 'newer' vehicles on the road will have the ancillary effect of lowering the number of fatalities in the existing fleet. NHTSA applies the same procedure of combining the non-fatal and PDO risks with VMT to calculate non-fatal and PDO incidents across alternatives.

As discussed in Chapter 4.3, we anticipate higher standards will slow fleet turnover which means miles that would have been driven in newer vehicles in our baseline will instead be driven in older vehicles in our alternatives. Consequently, more miles will be driven in older vehicles with a higher fatality risk.

Relatedly, the dynamic fleet share model discussed above in Chapter 4.2.1.3 impacts the relative shares of passenger cars and light trucks produced in each model year (because as the fuel economy levels of both improve, the improvements add more value to the latter, and this effect is amplified as fuel prices increase over time). Because cars and trucks have different fatality rates—in part due to their mass differences—variations in the market share of passenger cars and light-trucks across the alternatives will affect the estimated amount of fatalities, non-fatal injuries and PDO crashes. As light trucks, SUVs, and passenger cars respond differently to technology applied to meet the standards—namely mass reduction—fleets with different compositions of body styles will have varying amounts of fatalities. Since mass-safety effects are calculated by multiplying mass point-estimates by VMT, which implicitly captures the impact of the dynamic fleet share model, the estimates of mass-safety effects in the previous subchapter include the impact of vehicle prices and fuel savings on fleet composition.

7.5. Impact of Rebound Effect on Fatalities

The "rebound effect" is a measure of the additional driving that drivers may choose to undertake when the cost of driving declines. More stringent standards reduce vehicle operating costs, and in response, some consumers may choose to drive more. Driving more increases exposure to risks associated with on-road transportation, and this added exposure translates into higher fatalities. NHTSA has calculated this impact by estimating the change in VMT that results from alternative standards. Estimates of the rebound effect in the literature differ significantly. For this analysis, we use a rebound effect of 10 percent. A full discussion of the basis for selecting this rate is provided in Chapter 4.3.3.

Rebound miles are not imposed on consumers by regulation. They are a freely chosen activity resulting from reduced vehicle operational costs. As such, NHTSA believes a large portion of the safety risks associated with additional driving are offset by the benefits drivers gain from added driving. The level of risk internalized by drivers is uncertain. This analysis assumes that consumers internalize 90 percent of this risk, which mostly offsets the societal impact of any added fatalities from this voluntary consumer choice.

The actual portion of risk from crashes that drivers internalize is unknown. We suspect that drivers are more likely to internalize serious crash consequences than minor ones, and some drivers may not perfectly internalize injury consequences to other individuals, especially occupants of other vehicles and pedestrians. However, legal consequences from crash liability, both criminal and civil, should also act as a caution for drivers considering added crash risk exposure. NHTSA considered several approaches to estimating internalized crash risk. The first assumes that drivers value harm to themselves as well as legal liability for causing harm to others. It considers that all fatalities in single vehicle crashes are fully valued, that there is roughly a 50 percent chance that each driver would be the one killed in multi-vehicle crashes, and that there is roughly a 50 percent chance that each driver would be at-fault in a multi-vehicle crash that they survived. This produces an estimate of roughly 88 percent.

Another approach assumes that drivers fully value all damage in single vehicle crashes, and only discount property damage incidents in multi-vehicle crashes. Based on data in Blincoe, *et al.* (2015),[1124] multi-vehicle property-damage-only crashes account for about 7 percent of all societal crash costs, leaving 93 percent recognized under this approach. Yet another approach would assume drivers value injury crashes, but discount non-injury related costs such as property damage and traffic congestion. This approach results in roughly an 88 percent estimate of costs internalized. A fourth approach assumes that drivers fully value all quality-of-life losses associated with injury defined by the VSL, plus all personal expenses that result from external cost components not captured by the VSL. This approach results in an estimate that 86 percent of crash risk costs are internalized. Overall, while NHTSA recognizes this proportion is uncertain, we believe it is reasonable to assume that drivers internalize roughly 90 percent of the crash risk that results from added driving.

Note that none of these estimates account for net consumer surplus, implying that the full value of added driving gained or lost through the rebound effect is somewhat higher than these estimates. Based on this, we assume that 90 percent of the societal cost of additional motor vehicle crashes occurring due to rebound mileage is offset by the internalized acceptance of safety risk, and an additional portion is offset by added consumer surplus drivers obtain while assuming this risk. An estimate of this consumer surplus is provided in Chapter 6.1.5 of this document.

7.6. Fatalities, Non-Fatal Injuries, and PDO Crashes by Source

To calculate safety impacts, the model produces a dynamic total fleetwide safety impact that reflects the interaction of added rebound VMT, mass/safety impacts, and shifts in VMT among vehicles of different ages due to sales/scrappage impacts. Because these factors are interactive, the model does not predict which fatalities are “only” attributable to any of the three responses; it calculates a fleet response, and that fleet is the result of all those integrated modules. As the agency treats the safety costs differently for rebound-related fatalities, it is important to differentiate which fatalities are attributable to rebound. The agency also believes there is merit to parsing out mass-and fleet turnover-related responses.

Rebound safety impacts are computed by taking the difference in per vehicle rebound miles in the regulatory alternative and the reference baseline case, multiplied by the reference baseline fatality or injury rate per mile and reference baseline vehicle count. For example, fatalities due to rebound are computed as shown in Equation 7-3.

Equation 7-3: Fatalities Due to Rebound

$$Rebound_{alt}=\left[\frac{RVMT_{alt}\text{-}NRVMT_{alt}}{Veh_{Alt}}-\frac{RVMT_{base}\text{-}NRVMT_{base}}{Veh_{base}}\right]*FatalityRate_{base}*Veh_{base}$$

Where “RVMT” is VMT including rebound miles, “NRVMT” is VMT excluding rebound miles, “Veh” is the quantity of vehicles, and “Alt” represents the alternative being examined and “Base” is the reference baseline value. The rebound fatalities will show as zero for the reference baseline scenario, and all alternatives will show fatalities due to rebound miles using the reference baseline vehicle counts. The formula specifies vehicle counts to clarify that vehicle counts will change over time among alternatives.

The fatalities due to mass reduction use the reference baseline vehicle counts and per vehicle VMT of the reference baseline (including rebound). As with the fatalities attributable to rebound, the fatalities attributable to changes in mass reduction are calculated inherently as incremental values, relative to the reference baseline standards (the values will appear as zero for reference baseline standards in the outputs). The equation used to calculate the fatalities due to curb weight (mass)changes is as shown in Equation 7-4.

[1124] Blincoe, L. et al. 2015. The Economic and Societal Impact of Motor Vehicle Crashes, 2010. DOT HS 812 012. National Highway Traffic Safety Administration: Washington, D.C.

Equation 7-4: Fatalities Due to Curb Weight Change

$$\Delta CW\ Fatalities_{alt}=(FatalityRate_{alt}-FatalityRate_{base})*RVMT_{base}$$

NHTSA then computes the impacts of changing fleet turnover as the remainder.

Equation 7-5: Fatalities Due to Sales/Scrappage

$$Sales\&Scrap\ Fatalities_{alt}=(Fatalities_{alt}-Fatalities_{base})\ -Rebound\ Fatalities_{alt}\ -\ \Delta CW\ Fatalities_{alt}$$

The same process was used to calculate non-fatal and PDO crashes with their corresponding rates.

7.7. Valuation of Safety Impacts

Fatalities, nonfatal injuries, and property damage crashes are valued as a societal cost within the CAFE Model's cost and benefit accounting. Their value is based on the comprehensive value of a fatality, which includes lost quality of life and is quantified in the (VSL as well as economic consequences such as medical and emergency care, insurance administrative costs, legal costs, and other economic impacts not captured in the VSL alone. These values were first derived from data in Blincoe et al. (2015) and updated in Blincoe et al. (2023),[1125] adjusted to 2021 economics, and updated to reflect the official DOT guidance on the VSL.[1126] Nonfatal injury costs, which differ according to severity, were weighted according to the relative incidence of injuries across the abbreviated injury scale (AIS). To determine this incidence, the agency applied a KABCO/MAIS translator to CRSSKABCO based injury counts from 2017 through 2019. This produced the MAIS based injury profile. This profile was used to weight nonfatal injury unit costs derived from Blincoe et al (2023), adjusted to 2021 economics and updated to reflect the official DOT guidance on the VSL. Property-damaged vehicle costs were also taken from Blincoe et al. (2023) and adjusted to 2021 economics. VSL does not impact property damage. This gives societal values of $12.2 million for each fatality, $181,000 for each nonfatal injury, and $8,400 for each property damaged vehicle.

7.8. Summary of Safety Impacts

The previous discussion documents the methods used to determine the safety impacts of higher CAFE standards on vehicle occupants and their value to society. The resulting estimates are generated inside the CAFE Model and are detailed in Chapter 5 of the FRIA accompanying this final rule.

[1125] Blincoe, L. et at. 2023.The Economic and Societal Impact of Motor Vehicle crashes. Last revosed: 2019. Report No. DOT HS 813 403. National Highway Traffic Safety Administration.
[1126] Timothy, D. 2021. Departmental Guidance on Valuation of a Statistical Life in Economic Analysis. Mar. 23, 2021. Available at: https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis. (Accessed: Feb. 16, 2024).