

Final Technical Support Document

The Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule III for Model Years 2022 to 2031 Passenger Cars and Light Trucks

August 2026



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



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Table of Acronyms and Abbreviations

Abbreviation	Term
AALA	American Automotive Labeling Act
AC	air conditioning
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	base level aerodynamic drag technology
AERO10	aero drag reduction, level 2 (10% reduction)
AERO15	aero drag reduction, level 3 (15% reduction)
AERO20	aero drag reduction, level 4 (20% reduction)
AERO5	aero drag reduction, level 1 (5% reduction)
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
ALVW	adjusted loaded vehicle weight
AMFA	Alternative Motor Fuels Act of 1988
AMPC	Advanced Manufacturing Production Credit
AMTL	Advanced Mobility Technology Laboratory
Argonne	Argonne National Laboratory
AT	automatic transmissions
AT10	10-speed automatic transmission
AT5	5-speed automatic transmission
AT6	6-speed automatic transmission
AT7	7-speed automatic transmission
AT8	8-speed automatic transmission
AT9	9-speed automatic transmission
AWD	all-wheel drive
BAC	blood alcohol concentration

BCA Guidance	Benefit-Cost Analysis Guidance for Discretionary Grant Programs
BEA	Bureau of Economic Analysis
BEV	battery electric vehicle
BISG	belt integrated starter generator
BLS	Bureau of Labor Statistics
BMEP	brake mean effective pressure
BMW	BMW of North America, LLC
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
BW	brake wear
CAFE	Corporate Average Fuel Economy
CAGR	compound annual growth rate
CARB	California Air Resources Board
CARS	Car Allowance Rebate System
CBI	confidential business information
CD	charge-depleting
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
CNG	compressed natural gas
CO	carbon monoxide
CO ₂	carbon dioxide
CONFIG	engine camshaft configuration
CONV	conventional powertrain
COV	coefficient of variation
COVID-19	Coronavirus 2019 Public Health Emergency
CPI	Consumer Price Index
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
CVTL2	continuous variable transmission level 2HEG
CW	curb weight
CY	calendar year
DBS	dynamic brake support
DC	direct current
DCT	dual-clutch 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
DOT	U.S. Department of Transportation
DRI	Dynamic Research, Inc.
DSLI	advanced diesel engine with improvements
E.O.	Executive Order
EC	elemental carbon
ECU	engine control unit
eCVT	electronic continuously variable transmissions
EETT	Electrical and Electronics Technical Team
EF	emission factor
EGR	exhaust gas recirculation
EGU	electricity-generating units
EIA	U.S. Energy Information Administration
EIS	environmental impact statement
EISA	Energy Independence and Security Act of 2007
ELEC	electrification and hybridization
EPA	U.S. Environmental Protection Agency
EPCA	Energy Policy and Conservation Act of 1975
E-SBR	emulsion styrene butadiene
ESC	electronic stability control
ETDS	electric traction drive system
EV	electric vehicle
FARS	Fatal Accident Reporting System
FCA	Fiat Chrysler Automobiles
FCEV	fuel cell electric vehicle
FCIV	fuel consumption improvement value
FCW	forward collision warning
FE	fuel efficiency

FEOC	foreign entity of concern
FFV	flexible fuel vehicle
FHWA	Federal Highway Administration
FMVSS	Federal Motor Vehicle Safety Standards
FR	fatality rate
FRIA	final regulatory impact analysis
FTP	Federal Test Procedure
FWD	front-wheel drive
GCVW	gross combined vehicle 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
GWU	George Washington University
HCR	high compression ratio
HCRD	high compression ratio engine with cylinder deactivation
HCRE	high compression ratio engine with cooled exhaust gas recirculation
HDPUV	heavy-duty pickup trucks and vans
HEG	high efficiency gearbox
HEV	hybrid electric vehicle
HP	horsepower
HSS	high strength steels
HT	high towing
HWFET	highway fuel economy test
IAV	Ingenieurgesellschaft Auto und Verkehr
IC	internal combustion
ICCT	International Council on Clean Transportation
ICE	internal combustion engine
ICM	indirect cost multiplier
iEGR	internal exhaust gas recirculation
IIHS	Insurance Institute for Highway Safety
IMEP	indicated mean effective pressure
IOC	implicit opportunity cost
IRA	Inflation Reduction Act
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
LDV	light-duty vehicle
LDW	lane departure warning
LDWF	light-duty work factor
LFP	lithium iron phosphate
LIDAR	light detection and ranging
LIVC	late intake valve closing
LKA	lane keep assist
LOESS	locally estimated scatterplot smoothing
LT	light trucks
LTV	light trucks and vans
MAD	minimum absolute deviation
MAIS	maximum abbreviated injury scale
MAX	maximum values
MDPCS	minimum domestic passenger car standard
MIN	minimum values
MMBTU	million British thermal units
MOVES	motor vehicle emission simulator
mpg	miles per gallon
mph	miles per hour
MR	mass reduction
MR0	a base level of mass reduction technology
MR1	mass reduction - 5.0% of glider weight
MR2	mass reduction - 7.5% of glider weight
MR3	mass reduction - 10.0% of glider weight
MR4	mass reduction - 15.0% of glider weight
MR5	mass reduction - 20.0% of glider weight
MSRP	manufacturer suggested retail price
MY	model year
NA	naturally aspirated
NADA	National Automotive Dealers Association
NAS	National Academy of Sciences
NASEM	National Academies of Sciences, Engineering, and Medicine
NASS	National Automotive Sampling System
NBER	National Bureau of Economic Research
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
NHTSA	National Highway Traffic Safety Administration
NMC	nickel manganese cobalt
NOX	nitrogen oxide
NPRM	notice of proposed rulemaking
NRC	National Research Council
NRVMT	VMT excluding rebound miles
NVH	noise-vibration-harshness
NVPP	National Vehicle Population Profile
OB3	One Big Beautiful Bill Act
OC	off-cycle
OEM	original equipment manufacturer
OHV	overhead valve
OLS	ordinary least-squares
OMB	Office of Management and Budget
ORNL	Oak Ridge National Laboratory
PAEB	pedestrian automatic emergency braking
PC	passenger car
PDO	property damage-only
PDOV	property damage only vehicle
PEF	petroleum-equivalency factor
PFE	prohibited foreign entity
PFI	port fuel injection
PHEV	plug-in hybrid electric vehicle
PHEV50	PHEV with 50-mile range
PM	particulate matter
PM10	particulate matter 10 microns or less in diameter
PM2.5	particulate matter 2.5 microns or less in diameter
PRIA	preliminary regulatory impact analysis
RADAR	radio detection and ranging
RCD	reverse collision detection
RIA	regulatory impact analysis
ROI	return on investment
ROLL	tire rolling resistance
ROLL0	base level of rolling resistance improvement
ROLL10	tire rolling resistance, 10% improvement
ROLL20	tire rolling resistance, 20% improvement
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
SCO	synthetic crude oil
SEC	Securities and Exchange Commission
SEIS	supplemental environmental impact statement
SGDI	stoichiometric gasoline direct injection
SGDID	dual over-head cam engine and gasoline direct injection
SHEV	strong hybrid electric vehicle
SHEVP2	parallel strong hybrid electric vehicle
SHEVPS	power-split strong hybrid electric vehicle
SI	spark ignition
SIR	societal injury risk
SKIP	skip input in market data input file
SO ₂	sulfur dioxide
SOC	state of charge
SOHC	single overhead camshaft
SOX	sulfur oxide
SS12V	stop-start 12V hybrid electric vehicle
S-SBR	solution styrene butadiene rubber
STEO	EIA short-term energy outlook
SUV	sport utility vehicle
SwRI	Southwest Research Institute
TAR	technical assessment report
TCU	transmission control unit
TE	tailpipe emissions
TP	Tailpipe
TPMS	tire pressure monitoring system
TRANS	transmission technologies
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
TW	tire wear
TWR	trailer weight rating
U.S.	United States

U.S.C	Unites States Code
UDDS	Urban Dynamometer Driving Schedule
UE	upstream emissions
UMTRI	University of Michigan Transportation Research Institute
US06	A high acceleration aggressive driving schedule also identified as Supplemental Federal Test Procedures
VCR	variable compression ratio
VIN	vehicle identification number
VMT	vehicle miles traveled
VOC	volatile organic compounds
Volpe or Volpe Center	Volpe National Transportation Systems Center
VSL	value of a statistical life
VTG	variable turbo geometry
VTGE	variable turbo geometry (Electric)
VTTS	value of travel time savings
VVL	variable valve lift
VVT	variable valve timing
WF	work factor
WTP	willingness to pay
WTW	well-to-wheel

1. What Is NHTSA Analyzing, and Why?

The National Highway Traffic Safety Administration (NHTSA) is required by statute to set corporate average fuel economy (CAFE) standards for passenger automobiles and non-passenger automobiles (commonly referred to as “light trucks” or LTs)¹ for each model year (MY) at maximum feasible levels.² The agency also can amend previously established standards to a level that the agency determines is maximum feasible.³ In this action, NHTSA is amending standards for passenger automobiles and non-passenger automobiles produced in MYs 2022-2031.

The Energy Policy and Conservation Act of 1975 (EPCA) contains several requirements governing the scope and nature of CAFE standard setting. Among these, some requirements have been in place since EPCA was first signed into law in 1975, some were added in the Alternative Motor Fuels Act of 1988 (AMFA) and in the Energy Policy Act of 1992, and others were added in 2007 when Congress passed the Energy Independence and Security Act of 2007 (EISA). Most recently, One Big Beautiful Bill Act of 2025 (OB3) amended EPCA’s civil penalty provisions.⁴

Consistent with statutory and other requirements (including the Administrative Procedure Act, the National Environmental Policy Act (NEPA), various Executive Orders (E.O.) (such as E.O. 12866), and other administrative guidance (*e.g.*, Office of Management and Budget (OMB) Circular A-4), NHTSA conducts two analyses to estimate effects from different levels of CAFE standards. Additional discussion of why NHTSA conducts these analyses (*e.g.*, to fulfill EPCA, NEPA, and other administrative requirements), is found in the preamble, Final Regulatory Impact Analysis (FRIA), and Final Supplemental Environmental Impact Statement (Final SEIS) accompanying the final rule.

The first analysis, referred to as the standard-setting analysis (also known as “constrained” analysis) reflects statutory limitations on what NHTSA can consider 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; (2) shall consider dual-fueled automobiles to be operated only on gasoline or diesel fuel; and (3) may not consider, when prescribing a fuel economy standard, the trading, transferring, or availability of credits.”⁵ This Final Technical Support Document (Final TSD) explains the assumptions used in the standard-setting analysis supporting this action.

NHTSA also conducts an “unconstrained” CAFE Model analysis to evaluate, as required by NEPA, the reasonably foreseeable environmental effects of its proposed action and a reasonable range of alternatives

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
- Scenarios Input File
- Parameters Input File

¹ 49 U.S.C. 32901(17) and (18). Note that, while the term “light truck” is used primarily throughout the rulemaking documentation, due to the nature of the discussion of some topics (such as the later discussion on footprint curves and vehicle reclassification) it is pertinent to use the more technically accurate term “non-passenger automobile” from the statute in place of “light truck.”

² 49 U.S.C. 32902(a).

³ 49 U.S.C. 32902(c).

⁴ Pub. L. No. 119-21, 139 Stat. 72 (July 4, 2025).

⁵ 49 U.S.C. 32902(h).

that meet the purpose and need for the proposed action.⁶ The technical assumptions for environmental impact statement (EIS) simulations are discussed in the Final SEIS Appendix D.

In coordination with U.S. Department of Transportation's (DOT) Volpe National Transportation Systems Center (Volpe or the Volpe Center), NHTSA uses the CAFE Compliance and Effects Modeling System (usually shortened to the "CAFE Model" or just "the Model") to simulate and analyze manufacturers' potential responses to new CAFE standards and to estimate various impacts of those responses. NHTSA and Volpe coordinate to ensure that the CAFE Model's operation reflects the following statutory commands:

Corporate Average Standards: 49 U.S.C. 32902 requires that standards apply to the average fuel economy levels achieved by each manufacturer's fleets of vehicles produced for sale in the United States. The CAFE Model calculates the CAFE fuel economy of each manufacturer's fleet based on estimated production volumes and characteristics, including fuel economy levels, of distinct vehicle models that could be produced for sale in the United States.

Separate Standards for Passenger and Non-Passenger Automobiles: 49 U.S.C. 32902 requires DOT to set separate CAFE standards for passenger automobiles and non-passenger automobiles. The CAFE Model accounts for passenger and non-passenger automobiles separately, including differentiated standards and compliance.

Attribute-Based Standards: 49 U.S.C. 32902 requires DOT to define CAFE standards (separately for passenger and non-passenger automobiles) 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 as well as the mix and attributes of vehicles in the manufacturer's fleet. The CAFE Model accounts for such functions and vehicle attributes explicitly.

Separately Defined Standards for Each Model Year (MY): 49 U.S.C. 32902 requires DOT to set CAFE standards (separately for passenger and non-passenger automobiles) at the maximum feasible levels in each model year. The CAFE Model represents each model year explicitly and accounts for the production relationships between model years. For example, a new engine first applied to a given vehicle model/configuration in MY 2030 will most likely be retained in MY 2031; that same vehicle model reflects the fact that manufacturers do not apply brand-new engines to a given vehicle model every year.

Separate Compliance for Domestic and Imported Passenger Car Fleets: 49 U.S.C. 32904 requires the U.S. Environmental Protection Agency (EPA) to determine CAFE compliance for each manufacturer's fleets of domestic passenger cars and imported passenger cars separately. A passenger car is domestic or import based on the definitions provided in 49 U.S.C. 32904. The CAFE Model accounts explicitly for this requirement when simulating manufacturers' potential responses to CAFE 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 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. The projection is published at the time the standard is promulgated. The CAFE Model accounts explicitly for this requirement.

⁶ 42 U.S.C. 4332.

Statutory Basis for Stringency: 49 U.S.C. 32902 requires DOT to set CAFE standards for passenger and non-passenger automobiles at the maximum feasible levels, while considering technological feasibility, economic practicability, the need of the United States to conserve energy, and the impact of other motor vehicle standards of the Federal Government on fuel economy. The analysis and balancing of these factors necessarily change in light of current and projected economic and market conditions.

Accordingly, NHTSA has continued to expand and refine its qualitative and quantitative analysis to account for these statutory factors considering such conditions. For example, simulations of technology effectiveness estimates 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, with each optimized to a single vehicle model/configuration.

Civil Penalties for Non-compliance: 49 U.S.C. 32912 (and implementing regulations) prescribes a rate (in dollars per tenth of a mile per gallon) 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. When civil penalties are applicable (*i.e.*, when they are not set to a statutory value of \$0, as they currently are), the CAFE Model will calculate civil penalties for CAFE shortfalls. This capability can be implemented at the Model user’s choice.

Dual-Fueled and Dedicated Alternative Fuel Vehicles: For purposes of calculating CAFE levels used to determine passenger and non-passenger automobile 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. 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 or diesel-calculated fuel economy of dual-fueled AFVs) when NHTSA determines what levels of passenger and non-passenger automobile CAFE standards are maximum feasible. The CAFE Model is therefore run in a manner that excludes dedicated AFV technologies and limits the consideration of dual-fueled AFV’s fuel economy to their gasoline or diesel operation only. NHTSA operates the Model with this limitation when performing the analysis that is used to inform the setting of standards. The CAFE Model also can be run without this analytical constraint, and the agency does so in the NEPA analysis, as described below.

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” a maximum of five model years and “carried back” a maximum of three model years, transferred between regulated classes, and traded between manufacturers. However, credit use is also subject to specific limits: the statute 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 passenger automobiles. The CAFE Model has the capability to simulate manufacturers’ potential use of credits carried forward from prior model years or transferred from other fleets;⁷ however, this capability is not used in the standard-setting analysis because 49 U.S.C. 32902 prohibits consideration

⁷ The CAFE Model does not simulate the potential for manufacturers to carry CAFE credits back (*i.e.*, borrow) from future model years or acquire and use CAFE compliance credits from other manufacturers. NHTSA believes there is significant uncertainty in how manufacturers may employ these flexibilities in the future. For example, though it is reasonably foreseeable a manufacturer that over-complies in 1 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 and how manufacturers will trade credits with market competitors rather than making their own technology investments.

of manufacturers’ potential application of CAFE compliance credits when setting maximum feasible CAFE standards for passenger and non-passenger automobiles.

National Environmental Policy Act (NEPA): The Final SEIS accompanying this final rule documents changes in fuel use and emissions as estimated using the CAFE Model and documents corresponding estimates—based on the application of other models documented in the Final SEIS—of environmental impacts of the regulatory alternatives under consideration.

DOT has continued its ongoing effort to refine and expand capabilities of the CAFE Model for use in analyzing regulatory alternatives as considered in the NPRM and in this final rule. 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, perhaps even most, of the relevant assumptions in such an analysis are inevitably uncertain. To help address this, NHTSA updates the assumptions used in each successive CAFE analysis to reflect the current state of the world more accurately and to apply the best current estimates of future conditions. Accordingly, since the 2024 final rule, DOT made the following changes to the CAFE Model and its inputs for the NPRM:

- Updated the Market Data Input File to reflect the change in analysis fleet from MY 2022 to MY 2024;
- Updated algorithms and settings to remove statutorily prohibited inputs from the standard-setting analysis and to select between different types of analyses (*i.e.*, constrained and unconstrained);
- Updated the base dollar year from 2021\$ to 2024\$;
- Updated the capability to exclude plug-in hybrid electric vehicle (PHEV) electricity usage when PHEV fuel economy operation is in gasoline-only mode for standard setting;
- Updated the modeling capability to allow for vehicle reclassification;
- Updated the Market Data Input File to include vehicle reclassification;
- Updated the Model to use a bracketed costing approach to determine prices for the five levels of mass reduction;
- Updated the Scenarios Input File to phase out air conditioning (AC) and off-cycle (OC) fuel consumption improvement values (FCIVs);
- Updated the Market Data Input File to include advanced truck credits for MY 2024 vehicles, noting that those credits sunset after MY 2024 and are therefore only applicable to that 1 year;
- Updated the Parameters Input File to set the social cost of carbon at zero;
- Updated the Parameters Input File for changes in other economic variables;
- Updated the Scenarios Input File with an adjusted 45X, 30D, and 45W tax credit phase-out timeframe;
- Updated the Scenarios Input File to set civil penalties to zero;
- Updated selected economic assumptions:
 - Rebound elasticity;
 - Payback period;
 - Value of travel time per vehicle; and
 - Numerous other updates based on the 2025 Annual Energy Outlook (AEO).
- Updated emission rates based on default MOVES5 assumptions.

NHTSA has made further updates for the final rule analysis in response to comments received on the proposal, minor errors and omissions identified, and new information. These changes include:

- Updating the Market Data Input File based on comments received and other identified issues;

- Refresh and redesign years updated based on OEM announcements;⁸
 - U.S. dealership labor hours updated based on new data;
 - MR5 SKIP applied for light trucks;⁹
 - Vehicle platforms realigned to segregate EV variants;¹⁰
 - E85 fuel shares shifted to gasoline; and
 - Miscellaneous data entry anomalies addressed.
- Updating the Market Data Input File based on the changes to the vehicle reclassification implementation year.
- Updating the Scenarios Input File based on the changes to the petroleum-equivalency factor (PEF) interim final rule.¹¹
- Updating the Scenarios Input File with an adjustment to the 45X battery tax credit implementation through 2032.
- Updating economic and emissions assumptions in the Parameters Input File:
 - Numerous updates based on the 2026 AEO; and
 - Updating selected emission rates based on GREET 2025 and updated input assumptions to MOVES5.
- Modifying the CAFE Model to expand capabilities and implement minor corrections:
 - Update emissions calculations to report domestic quantities in addition to global quantities;
 - Adjust calculations of forgone consumer sales surplus to include vehicle and battery tax credits and correct a minor error in calculation;
 - Refine battery tax credit calculations to use per-vehicle battery capacity based on Argonne simulation data;
 - Improve insurance cost calculation by transitioning from sales-weighting to weights based on the surviving fleet at each age; and
 - Various adjustments to allow for additional sensitivity case analysis, as discussed in FRIA Chapter 9.

These changes reflect NHTSA’s longstanding commitment to the ongoing refinement of its approach to estimating the potential impacts of new CAFE standards. Additional information on the CAFE Model can be found in the CAFE Model Documentation.

These and other updated analytical inputs are discussed in detail in the remainder of this Final TSD as follows:

Chapter 1 of this Final TSD explains how NHTSA develops footprint-based curves for the regulatory alternatives that represent different levels of possible CAFE stringency.

⁸ NHTSA reviewed manufacturers’ announcements regarding nameplate refresh and redesign for MYs 2025 and 2026. If the actual refresh or redesign misaligned with what was in the Market Data Input File for the NPRM, NHTSA updated the Market Data Input File to reflect the actual refresh or redesign year of the nameplate. The specific updates for nameplate refresh and redesign years can be found in Docket No. NHTSA-2025-0491 titled, “2026_FRM_Refresh_Redesign_Update.xlsx.”

⁹ See Final TSD Chapter 3.4.3 for discussion on the MR5 SKIP.

¹⁰ To ensure EVs were excluded from the analysis, EV platforms were realigned to not share a powertrain with an ICE, SHEV, or PHEV variant. If a vehicle platform included both ICE and EV powertrains, the EV variant(s) were assigned its own platform.

¹¹ 91 FR 7810 (Feb. 19, 2026).

Chapter 2 describes the development of the inputs required by the Model, specifically detailing the analysis fleet, technology effectiveness values, technology adoption and availability, technology costs, and other inputs.

Chapter 3 describes vehicle technology options, fleet assignments, adoption features and logic, technology effectiveness, and technology costs within the Model in detail.

Chapter 4 describes consumer responses to manufacturer compliance strategies, including macroeconomic representations of 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 upstream and tailpipe emissions and how health effects result from those changes.

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 and the impact of these safety effects.

1.1. Footprint-Based Standards

EPCA, as amended by EISA, requires that NHTSA prescribe CAFE standards for passenger and non-passenger automobiles based on one or more vehicle attributes related to fuel economy and express the standards in the form of a mathematical function.¹² As in the five CAFE rulemakings since 2010, NHTSA is setting CAFE standards as a function of vehicle footprint, which is a vehicle attribute with an observable correlation to fuel economy. NHTSA defines a vehicle's footprint, per 49 CFR 523.2, as the vehicle's track width measured in inches multiplied by the vehicle's wheelbase measured in inches, divided by 144, and then rounded to the nearest one-tenth square foot. Thus, the finalized regulatory alternatives for passenger and non-passenger automobiles take the form of fuel economy targets expressed as functions of vehicle footprint.

Though there are many vehicle attributes related to fuel economy, NHTSA has chosen to use vehicle footprint as the relevant attribute since MY 2011, the first year of CAFE standards set under EISA. 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) may be better correlated to fuel economy, and even though the 2021 National Academy of Sciences (NAS) Report suggested adding another attribute.¹³

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,¹⁴ noting that smaller and lighter vehicles incentivized by those standards could be less safe for their occupants. Since

¹² 49 U.S.C. 32902(b)(3)(A).

¹³ National Academies of Sciences, Engineering, and Medicine, *Assessment of Technologies for Improving Fuel Economy of Light-Duty Vehicles – 2025-2035*, National Academies Press: Washington, D.C. (2021), available at: <https://nap.nationalacademies.org/catalog/26092/assessment-of-technologies-for-improving-light-duty-vehicle-fuel-economy-2025-2035> (accessed: May 18, 2026) (hereinafter, “2021 NAS report”).

¹⁴ Transportation Research Board and National Research Council, *Effectiveness and Impact of Corporate Average Fuel Economy (CAFE) Standards*, National Academies Press: Washington, D.C., pp. 5, 12 (2002), available at: <https://nap.nationalacademies.org/catalog/10172/effectiveness-and-impact-of-corporate-average-fuel-economy-cafe-standards> (accessed: May 18, 2026) (hereinafter, “2002 NAS Report”).

that report, and because prior litigation raised the possible safety effects associated with CAFE standards, NHTSA has sought to set CAFE standards with an eye toward these possible effects. Because 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 (footprint, mass, or another dimensional measure).

As discussed in NHTSA's 2009 final rule for MY 2011 vehicles,¹⁵ 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 and wiring. Mass-based standards also can 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 thus 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 frontal 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 less likely to incentivize design decisions that solely affect applicability of a particular standard. Though manufacturers may adjust track width, wheelbase is more difficult and expensive to change, at least outside a planned vehicle redesign, and cannot easily be adjusted year to year, unlike mass. Among other things, changes in footprint can affect vehicle dynamics, for example, requiring re-evaluation of compliance with certain Federal Motor Vehicle Safety Standards (FMVSS) and safety system performance.

The question has also arisen of whether NHTSA should instead consider multi-attribute standards for CAFE, such as those that also depend on a combination of mass, torque, power, towing capability, or off-highway 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 involved in applying an attribute-based standard.¹⁶ At the same time, footprint-based standards can be structured in a way that furthers the statutory goals of EPCA and EISA by not creating inappropriate incentives to increase vehicle size in ways that could increase fuel consumption.

As mentioned above, NHTSA continues to conclude that footprint is the most appropriate vehicle attribute for fuel economy standard setting in accordance with section 32902. NHTSA did not reconsider whether footprint should be the appropriate attribute or consider a multi-attribute standard for this rulemaking. Instead, NHTSA is reconsidering whether the existing mathematical function connecting footprint and fuel economy, also required by section 32902, is still sufficiently representative of that

¹⁵ See 74 FR 14196 (Mar. 30, 2009).

¹⁶ General policy goals include 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.

relationship. The following section discusses NHTSA’s reconsideration of the mathematical function,¹⁷ relating fuel economy and footprint for this final rule.

1.2. Standards Defined by a Mathematical Function

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,” 49 U.S.C. 32902(b)(3)(A) provides discretion regarding not only the selection of the attribute(s), but also regarding the nature of the function. NHTSA is continuing to use vehicle footprint as the attribute “related to fuel economy” to establish passenger automobile and non-passenger automobile standards. However, NHTSA reconsidered the mathematical functions used 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 not so precise as to yield one single possible function that connects the two factors. The decision of how to specify this mathematical function therefore requires some amount of judgment. The function can be specified with a view toward achieving different levels of energy conservation or levels of technology application, avoiding adverse effects on safety, reducing disparities in compliance burdens across manufacturers, and preserving consumer choice among different types and sizes of vehicles, among other aims.

NHTSA has consistently used a constrained linear function in previous rulemakings. In NHTSA’s use of the constrained linear function, the constraints are also called “cutpoints” and set maximum and minimum fuel efficiency (FE) targets for the vehicle fleets. The following are technical concerns and policy trade-offs that NHTSA has previously considered in selecting curve shapes applied in past CAFE rulemakings:

- Steeper footprint-based standards (in the sense that standard levels decrease sharply with increasing footprint) may create incentives to upsize vehicles because small changes in vehicle footprint would result in a significant change in the resulting fuel economy. This could result in manufacturers oversupplying vehicles of certain footprints beyond what the market would otherwise demand and thus increase the possibility that fleetwide (or total) fuel-savings benefits will be artificially diminished.
- Flatter footprint-based standards (in the sense that standard levels decrease gradually with increasing footprint) would result in smaller differences between the fuel economy targets for smaller and larger vehicles, increasing the risk that standards cannot be met by larger vehicles without significant cost. This could make larger vehicles unaffordable, or result in their being removed from the market, or reducing the supply of options for consumers who may need the utility of a larger vehicle.

Regarding the “constraints” in the constrained linear functions, which NHTSA applies as “cutpoints”—locations in the change of the slope of the fuel economy target curves—the following technical concerns and policy trade-offs apply:

- Given the same industry-wide average required fuel economy, moving small-vehicle constraints up, in terms of fuel economy, discourages the introduction of small vehicles, and reduces the incentive to downsize small vehicles as a means of achieving compliance with the CAFE standards.
- Given the same industry-wide average required fuel economy, moving large-vehicle constraints down, in terms of fuel economy, encourages the introduction of larger vehicles and extends the range over

¹⁷ Also represented visually as the footprint “curves” that define fuel economy standards, set in terms of fuel consumption, which is the inverse of fuel economy.

which the targets decline with increasing footprint, thereby discouraging downsizing in ways that could compromise overall highway safety.

Since the 2012 final rule, NHTSA has retained and used the same curve shapes (meaning the same constrained linear functions, only rescaling parameters) in its CAFE rulemakings. NHTSA also noted previously that the agency would continue to explore reasonable and appropriate changes to the curve shapes in a future rulemaking.¹⁸ For this analysis, NHTSA updated the shapes of the footprint curves based on a re-examination of the relationship between footprint and FE and ongoing trends in fleet share¹⁹ and vehicle reclassification²⁰ using the most recent fleet data available.²¹

In the remainder of this chapter, NHTSA examines policy concerns relevant to developing target curves that define the MYs 2022-2031 CAFE standards. This chapter discusses the technical work involved in re-examining the mathematical functions for this rulemaking, expanding on similar historical analyses NHTSA had performed, the definition and selection of data, and statistical curve-fitting methodologies used to arrive at final curves. Further, detailed discussion of estimation methodology also can be found in a docket memorandum.²²

1.2.1. Mathematical Functions for this Final Rule

Pursuant to 49 U.S.C. 32902(b), NHTSA sets separate standards for passenger automobiles and for non-passenger automobiles. NHTSA creates a mathematical function that defines a fuel economy performance target for each unique footprint value. Using the functions, manufacturers calculate CAFE standards for each fleet in each model year based on the footprints and production volumes found in each fleet. The functions are descending in slope, meaning larger footprint vehicles will be subject to lower mile(s)-per-gallon (mpg) targets than smaller footprint vehicles. This is an appropriate characteristic, regardless of the specific function selected, because smaller vehicles are typically capable of achieving higher levels of fuel economy relative to larger vehicles.

NHTSA uses a manufacturer's final model year production sales volumes to calculate the final standards for a given model year.²³ The agency's calculation of a manufacturer's fleet average standards, as well as the average performance of a manufacturer's fleet at the end of the model year, is based on the production-weighted average target and performance of each model in its fleet. As discussed in prior rulemakings, a manufacturer may have some vehicle models that exceed their target and some that are below their target. Compliance is determined by comparing the calculated fleet production-weighted harmonic average standard with calculated fleet production-weighted harmonic average performance.

As stated above, NHTSA continues to use constrained linear target functions for both the passenger and non-passenger automobile target curves. In the following equations, *TARGET* is the fuel economy target applicable to vehicles of a given footprint in square feet (*FOOTPRINT*). The upper constraint, *a*, and the lower constraint, *b*, are specified in mpg; these values are the reciprocal of the lower and upper

¹⁸ See 89 FR 52540 (June 24, 2024).

¹⁹ See trends discussion in Chapter 1.2.4.

²⁰ Vehicle reclassification is further discussed in Final TSD Chapter 2.7 as well as preamble Section VI.

²¹ MY 2022 data are used to create the new fuel economy versus footprint curve shapes for MYs 2022-2029 standards, and MY 2024 fleet data are used to create the new fuel economy versus footprint curve shapes for MY 2030 standards and beyond.

²² See NHTSA's Re-evaluation of its Attribute Function and Development of Proposed Standards, which can be found in the rulemaking docket (NHTSA-2025-0491) by filtering for Other.

²³ "Final" is used here to indicate end of year, or final compliance values. These values are supplied to NHTSA by EPA.

constraints, respectively, translated from gallons per mile (gpm). The slope, c , and the intercept, d , of the linear portion of the curve are specified as gpm per change in square feet and gpm, respectively.

NHTSA's implementation of the constrained linear target function for determining a target fuel economy is shown in Equation 1-1 and Equation 1-2. The maximum (MAX) function in the denominator will first find the maximum of the fitted line at a given footprint value and the lower constraint in gpm units. If the fitted line is below the lower constraint, it is replaced with the value of the lower constraint, so that the target in mpg will be the reciprocal of the lower constraint in mpg, or simply, a . If, however, the fitted line is not below the lower constraint, the fitted value is returned from the MAX function, and the minimum (MIN) function is then applied and takes the minimum value of the upper constraint (in gpm) and the fitted line. If the fitted value is below the upper constraint, it is between the two constraints, and the fitted value is appropriately returned from the MIN function, making the overall target in mpg the reciprocal of the fitted line in gpm. If the fitted value is above the upper constraint, the upper constraint is returned from the MIN function, and the overall target in mpg is the reciprocal of the upper constraint in gpm, or simply, b .

The slope and intercept are specified as gpm per sq. ft. and gpm (instead of mpg per sq. ft. and mpg) because they directly account for fuel consumption (as opposed to its reciprocal).

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

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

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

Where:

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

a is the lower constraint value, or minimum fuel economy target (in mpg),

b is the upper constraint, or maximum fuel economy target (in mpg),

c is the slope (in 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.

Again, 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 FRIA Chapter 3 in graphs displaying the passenger car target function in each model year for each regulatory alternative. The values for the variables a , b , c and d are also presented in FRIA Chapter 3.

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

Equation 1-2: Non-Passenger Automobile Fuel Economy Footprint Target Curve

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

Where:

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

Parameters a , b , c , and d function identically to those used for passenger cars but take values specific to non-passenger automobiles.

Like the passenger automobile target function, the resultant functional form and variable values for non-passenger automobiles are shown in FRIA Chapter 3 in graphs displaying the non-passenger automobile target function in each model year for each regulatory alternative. Though the general form of the target function equation is the same for both passenger and non-passenger automobiles and for each model year, the parameters used to calculate specific standards are different for each fleet and model year.

No individual vehicle is required to meet the specific applicable fuel economy target because compliance is determined based on fleet average performance. In this respect, CAFE standards are unlike, for example, FMVSS and certain vehicle criteria pollutant emissions standards, where each individual vehicle must meet the requirements. Instead, CAFE standards apply to the average fuel economy levels achieved by manufacturers' entire fleets of vehicles produced for sale in the United States. 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 fleet standard, or fall short of their target under attribute-based standards) while others "over-comply" as long as, on average, a manufacturer's overall fleet remains in compliance.

For passenger automobiles and non-passenger automobiles, the required CAFE standard 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 the individual vehicle models in the fleet, as shown in Equation 1-3.

Equation 1-3: 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 configurations i produced for sale in the United States,

and

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

The following sections give a brief history of mathematical functions used for previous CAFE rules as background to the subsequent discussion of how the agency reconsidered the mathematical functions for this final rule.

1.2.2. Mathematical Functions from Prior Rules

NHTSA has been given discretion under EPCA and EISA in choosing the mathematical functions used to define the CAFE standards, and those choices are informed by data. When the relevant data are defined, interpreted, and fitted to a function curve, NHTSA considers statutory factors and relevant policy considerations. This subchapter summarizes the methodologies and policy concerns that were considered in developing target curves applied in previous CAFE rulemakings.

1.2.2.1. 2006 Final Rule and 2008 NPRM for MY 2008+ and MY 2011+ (Constrained Logistic)

In the 2006 final rule for MYs 2008-2011 light truck standards, NHTSA examined a range of potential functional forms and concluded that, compared to other considered forms, the constrained logistic form provided the expected and appropriate trend (decreasing fuel economy as footprint increases) but avoided creating “kinks” that the agency was concerned would provide distortionary incentives for vehicles on either side of the kink points.²⁴ In the 2008 Notice of Proposed Rulemaking (NPRM) for the MYs 2011-2015 standards (for which NHTSA subsequently finalized standards for MY 2011 only),²⁵ NHTSA estimated fuel economy levels by footprint from the MY 2008 fleet after normalization for differences in technology but did not make adjustments to reflect other vehicle attributes (*e.g.*, power-to-weight ratios).²⁶ Starting with the technology-adjusted passenger car and light truck fleets, NHTSA used minimum absolute deviation (MAD) regression without sales-weighting to fit a logistic form as a starting point to develop mathematical functions defining the standards. NHTSA then identified footprints at which to apply minimum and maximum values (rather than letting the standard functions extend without limit) and transposed those functions vertically (*i.e.*, on a gpm basis, uniformly downward) to produce the promulgated standards.

1.2.2.2. 2010 Final Rule for MYs 2012-2016 Standards (Constrained/Piecewise Linear)

The agency re-evaluated potential methods for specifying the mathematical relationship between footprint and fuel economy for the MYs 2012-2016 final rule. For that analysis, NHTSA used the same MY 2008 data that were used to generate the MY 2011 standard function. NHTSA found that the constrained logistic form, previously used, introduced a steep mid-section that could provide manufacturers with an undue incentive to increase the footprint of mid-size passenger cars and was therefore ruled out.²⁷ Further analysis indicated a range of methods to fit the curves was reasonable, and a MAD regression without sales-weighting on a technology-adjusted car and light truck fleet was used to fit a linear equation. This equation served as the starting point to develop mathematical functions defining the standards. The agency then determined minimum and maximum footprint values, beyond which the curves flattened, to prevent the sloped standards equations from extending without limit. The attribute-based targets for passenger cars and light trucks NHTSA set in the 2010 final rule are a vertical transposition (*i.e.*, the curve slope remains and cutpoints remain constant, but curve amplitudes were changed) of these

²⁴ See 70 FR 51414, 51414-51466 (Aug. 30, 2005) for NHTSA discussion of “kinks” in the MYs 2008-2011 light truck CAFE standards (there described as “edge effects” in the 2005 NPRM). A “kink,” as used here, is a portion of the curve where a small change in footprint results in a disproportionately large change in stringency.

²⁵ See 73 FR 24352, 24352-24487 (May 2, 2008) for NHTSA discussion on estimating fuel economy levels by footprint after normalization for differences.

²⁶ See 74 FR 14363, 14363-14370 (Mar. 30, 2009) for NHTSA discussion of curve fitting in the MY 2011 CAFE final rule.

²⁷ This behavior was noted when the candidate methodology was applied to MY 2011 standards and beyond. For additional detail, see 75 FR 25362 (May 7, 2010).

constrained/piecewise linear functions. This transformation was accomplished by multiplying the initial curve by a single factor for each model year standard.²⁸

1.2.2.3. 2012 Final Rule for MYs 2017-2021 (Constrained Linear)

The mathematical functions finalized in 2012 for MYs 2017 and beyond changed somewhat from the functions used in the 2010 final rule to define the MYs 2012-2016 standards. These changes addressed comments from stakeholders and accounted for technical concerns and policy goals NHTSA had prioritized given the increased consequential uncertainty of setting standards for model years further into the future.²⁹ Recognizing the concerns raised by full-line original equipment manufacturers (OEMs), the agency concluded that continuing increases in the stringency of the light truck standards would be more feasible if the light truck curve for MYs 2017 and beyond was steeper than the MY 2016 truck curve and the right (large footprint) cutpoint was extended only gradually to larger footprints over time. To accommodate these considerations, the 2012 final rule finalized the slope fit to a simulated MY 2008 fleet using a sales-weighted, ordinary least-squares (OLS) regression; the simulated fleet included a weight-to-footprint ratio adjustment and included smoothed (*i.e.*, more uniform) technology application than in the observed baseline fleet.³⁰ Information from an updated MY 2010 fleet was also considered to support this decision. Any subsequent vertical shifts in the light truck curve (in mpg, rather than gpm terms) were paired with adjustments to the right cutpoint; this cutpoint was set to reach its maximum in MY 2022. The updates to the cutpoints, as discussed here, only applied to the non-passenger (light truck) fleet standards.

1.2.2.4. Footprint Curves for the 2020 SAFE Rule, 2022 Final Rule, and 2024 Final Rule

NHTSA maintained and implemented the 2012 final rule footprint curves for passenger and non-passenger automobiles for the 2020, 2022, and 2024 final rules. During these rulemakings, NHTSA recognized that vehicle manufacturers had continued to reduce their offerings of smaller footprint vehicles, increase their offerings of larger footprint vehicles, and sold many small to mid-size crossovers and sport utility vehicles (SUVs). Though this trend changed the mix of vehicles in the fleet, it did not appear that the underlying statistical relationship between footprint and fuel economy relative to that of the MY 2008 fleet changed enough over time “to warrant a detailed re-examination of that relationship.”³¹ The 2020 rule did reconsider the footprint curve shapes using the newest available data at the time (MY 2016 fleet) and included an analysis using various statistical methods, weighting schemes, and data adjustments; however, the findings ultimately supported the decision to retain the curve shapes developed for the 2012 final rule.³²

²⁸ See generally 74 FR 49491, 49491-49496 (Sept. 28, 2009); 75 FR 25357, 25357-25362 (May 7, 2010).

²⁹ The MYs 2012-2016 final standards were issued April 1, 2010—putting 6.5 years between its issuance and the last affected model year, while the MYs 2017-2021 final standards were issued August 28, 2012—giving just more than 9 years between issuance and the last affected final standards.

³⁰ Available technology adoption was simulated for the fleet, producing the most efficient versions of each model using available technologies. This ensured that application of fuel-saving technologies was more uniform across vehicles in the fleet, limiting the influence of heterogeneity created by emerging technologies that were not widely available at the time.

³¹ See 86 FR 49602, 49631 (Sept. 3, 2021). Moreover, NHTSA believed it was unlikely any potential benefit of changing the shape of the footprint curves (when already significantly changing standard stringency) would outweigh the costs of doing so.

³² See 85 FR 24174, 24174-25278 (Apr. 30, 2020) for NHTSA’s discussion on reconsidering curve footprint curve shapes.

1.2.3. Reconsideration of the Mathematical Functions

1.2.3.1. Motivation for Reconsidering the Mathematical Functions

When NHTSA proposes or amends standards in a discrete regulatory action, the agency assumes the underlying relationship of fuel consumption (in gpm) to vehicle footprint does not change over the range of model years covered by the standards.³³ However, the agency recognizes that this relationship may evolve over the longer term and should be evaluated and updated periodically. Changes in fleet composition, consumer demand, and technology offerings could alter the observed association between these two vehicle characteristics. For example, if certain technologies become more effective or more marketable for some types of vehicles, their application trends may not be uniform over the range of vehicle footprints. In addition, the evolution of overall fleet composition, like the changes noted in Chapter 1.2.2.4, could modify the fleetwide fuel economy and footprint relationship. Any adjustments to the definitions of passenger and non-passenger automobiles, such as those included in this final rule, also require re-evaluation of the mathematical functions.

For these reasons, NHTSA reconsidered the curve shapes used for this final rule by analyzing the most recent available data. The agency explored a range of regression techniques and descriptive statistical analyses to examine the reported fleet data. NHTSA also conducted a separate vehicle simulation analysis to inform updates to the mathematical functions. These analyses revealed significant changes to the composition of the fleet since MY 2008, as well as notable changes in the application of fuel-saving technologies.

As in the 2012 final rule, NHTSA finds the effects of these changes on the estimated footprint curves somewhat ambiguous and dependent on the methodology used to estimate the relationship. When comparing estimates that use similar methodologies, the observed relationship in both fleets is on average “flatter” than that found in the MY 2008 fleet (*i.e.*, on average, fuel economy did not vary as much across footprint levels in the recent data compared to the MY 2008 fleet). Vehicle reclassification also has a significant effect on the mathematical relationship between footprint and fuel consumption for passenger and non-passenger automobiles. For the above reasons, NHTSA updated the mathematical functions from the values employed in the 2012 final rule.

1.2.3.2. Analysis Methods and Specifications

NHTSA performed descriptive statistical analyses using manufacturer-reported data for the MY 2022 fleet and MY 2024 fleet.³⁴ To isolate the relationship between fuel economy and footprint and to maintain general consistency with analysis of past rules, the agency excluded some vehicles from the analysis and applied weighting and other controls to the fuel consumption and footprint data. Consistent with past approaches, the analysis for this final rule excluded all diesel engine vehicles because gasoline-fueled vehicles are expected to remain the dominant combustion engine technology in the analysis fleet over the regulatory time horizon. In addition, NHTSA excluded plug-in hybrid-electric vehicles (PHEVs), battery electric vehicles (BEVs), and fuel cell electric vehicles (FCEVs) from this analysis due to statutory constraints. The agency also evaluated numerous methodological options, as presented in Table 1-1 below. NHTSA considered all possible combinations of these assumptions, producing footprint

³³ The relationship between fuel consumption and vehicle footprint informs the mathematical function specifying CAFE standards. The content of this chapter refers to this relationship informally as the “footprint curve.” Though these are “fuel economy” (mpg standards, the functions are specified in terms of “fuel consumption” (gpm). As this chapter discusses the functional form of the standards, text and plots are shown in fuel consumption space.

³⁴ MY 2022 data are used to create the new fuel economy versus footprint curve shapes for MYs 2022-2029 standards, and MY 2024 fleet data are used to create the new fuel economy versus footprint curve shapes for MY 2030 standards and beyond.

curves for each combination. The remaining subsections of this chapter contain additional detail on each category. Additional technical details are available in a memo to the docket.³⁵

Table 1-1: Summary of Methodological Approaches Considered for Assessing Footprint Curves

Category	Type	Description	Key Considerations
Regression types	Ordinary Least-Squares (OLS)	Regression solution that minimizes squared errors	Describes the average relationship between footprint and fuel economy; outliers receive additional weight.
	Minimum Absolute Deviation (MAD)	Regression solution that minimizes absolute errors	Describes the median relationship between footprint and fuel economy; does not give outliers as much weight as OLS.
Datapoint weighting	Production weights	Data weighted by production volumes of each vehicle model	High production, mass market vehicles have a greater influence on the footprint curve form than vehicles with lower production levels.
	Model weights	Each vehicle model receives equal weighting	Estimates treat all vehicle model lines equally and therefore measures footprint curves based on vehicle model offerings (<i>i.e.</i> , ignores the effect of sales volume).
Vehicle technology levels	Existing technology	Analysis dataset contains information on current observed technology in the baseline fleet	Represents the existing market, including demand factors; retains existing heterogeneity in technology application across the fleet.
	Simulated maximum technology ³⁶	Analysis dataset derived from simulation modeling that assumes maximum allowable technology, with multiple candidates for technology limits.	Represents the “engineering” relationship between fuel consumption and footprint by limiting heterogeneity in current technology application across the fleet (<i>i.e.</i> , represents the technology frontier for the current fleet).
Controls	Curb weight (CW) to footprint	Removes variation in fuel consumption caused by above/below average CW-to-footprint.	Limits noise in the observed relationship between fuel consumption and footprint that is introduced by manufacturers optimizing other attributes (<i>e.g.</i> , increased acceleration, and therefore also affect fuel economy); accounts for some of the variation by body style.
	Horsepower (HP) to curb weight (CW)	Removes variation in fuel consumption caused by above/below average HP-to-CW.	
	Both	Removes variation in fuel consumption caused by	

³⁵ See NHTSA’s Re-evaluation of its Attribute Function and Development of Proposed Standards, which can be found in the rulemaking docket NHTSA-2025-0491.

³⁶ The maximum technology fleet was simulated with the CAFE Model, assuming an MY 2024 fleet and maximum allowable technology application.

		above/below average CW-to-footprint and HP-to-CW.	
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1.2.3.2.1. Regression Types

The statistical analysis for evaluating updated footprint curves implemented ordinary least squares (OLS) and minimum absolute deviation (MAD) regression methods. The methods differ in their treatment of outliers in the analysis dataset; the MAD approach is generally applied to mitigate the effect of outliers in a dataset, while outliers play a relatively larger role in determining curve shapes under OLS regression.

In the analysis of footprint curves, vehicles are considered outliers when their fuel consumption deviates from most other vehicles with similar footprints. In typical data settings, these outlier observations could be the result of mismeasurement and would require special treatment. However, the footprint curve data used for this analysis is certification data, and the chance of large measurement errors is small. Thus, these observations are most likely outliers due to their unique vehicle designs and technology attributes. Examples of outlier vehicles include performance vehicles, vehicles with high ground clearance, or those with poor aerodynamic designs (*e.g.*, boxy designs). Though these vehicles may represent outliers in terms of fuel economy, each are feasible on-highway vehicle designs, and the agency concluded they should be included in the regression analysis.

Absent clear reasons to exclude these observations, the choice of regression method determines the magnitude of their effect on setting the footprint curve specifications. Both methods were used in prior final rules. NHTSA employed MAD regression in the 2010 final rule to address the effects of outlier observations representing vehicles with emerging technologies that were not yet broadly available throughout the fleet. The agency changed its approach in the 2012 final rule and relied on OLS estimation. Here, the agency addresses outliers by using a combination of datapoint weighting, simulated technology application, and control variables. As in the 2012 and subsequent final rules, NHTSA concludes that the OLS regression framework is the more appropriate method for estimating the footprint curves. As discussed in subsequent sections, technology-based exclusions and data normalization via the application of controls reduced the effect that outlier observations could have on the curve fits, and the agency determined it was not necessary to address these concerns further via MAD regression.

1.2.3.2.2. Datapoint Weighting

NHTSA considered two approaches to weighting observations in the analysis dataset: production-level weighting and model-level weighting. Vehicle models, as defined in the CAFE Model input fleet, with high production volumes play a larger role in determining the footprint curve estimates than vehicle models with lower production volumes under a production-weighting scheme. Conversely, each model is weighted equally when using model-level weights. Table 1-2 illustrates the difference in these weighting methods for two example vehicle-lines. The table shows the F-150 would have more than twice the influence under the model-weighting scheme, where the F-150 has 310 different model variants versus the Silverado that has 130 model variants. Contrast this with a more even influence between the vehicles under the production-weighting scheme, where the difference in production volumes between the pickups is only about 30 percent.

Table 1-2: Sample Production Volumes and Model Counts from CAFE Model Inputs, MY 2022 Fleet

	Production volume (units)	Model Count
Ford F-150	491,000	310
General Motors (GM) Silverado	369,000	130
Ratio (F-150:Silverado)	1.33	2.38

The agency did not use production-level weighting in the 2010 final rule analysis of curve shapes. The decision not to perform production-level weighting reflected the agency’s judgment that each vehicle model provides an equal amount of information concerning the underlying relationship between footprint and fuel economy. At the time, the agency used projected sales numbers for two vehicles as an example to justify the choice of model weighting: Toyota’s 2WD Sienna (187,000 units predicted to be produced in MY 2016) and Prius (268,000 units predicted to be produced in MY 2016). These production volumes mean that the Sienna and Prius would have received significant weight in a production-weighted analysis compared to the non-trivial number of low-production vehicles. In the projected MY 2016 data, the agency also identified 27 light truck models with fewer than 100 units produced, and 29 passenger car models with fewer than 100 units produced; had the agency chosen a production-weighted approach those models with extremely low production volumes would have received minimal weight. In the 2012 final rule, the agency changed its approach and instead used production weighting, pointing to the fact that in some cases mass market vehicles differed significantly in the number of unique models available but not in terms of sales. In cases like this, subtle variations between models for a single mass market vehicle likely reflect differences in the other features of vehicles, rather than variation in their footprints or FE. As a result, model weighting would tend to overweight vehicles with many of these options available.

Both production-weighting and model-weighting present advantages and trade-offs. Ultimately, some of the problems with model-weighting noted in the 2012 final rule appear to be present still, as seen in Table 1-2. Though production-weighting confers more importance on mass market vehicles without providing any additional engineering information about the trade-off between footprint and FE for *all* vehicles, they do provide important information about how this relationship holds for mass market vehicles. For example, if limiting this trade-off requires additional manufacturing costs or changes to vehicle designs that would limit the commercial prospects of a vehicle unduly, then they are unlikely to be made for mass market vehicles but may be made for smaller production vehicles. Because NHTSA is setting standards for the entire light-duty fleet, the implicit trade-off it offers to manufacturers through the footprint curve should not be infeasible for mass market vehicles.

Figure 1-1 and Figure 1-2 show the OLS-estimated relationship for passenger cars and light trucks, respectively, in the MY 2022 fleet. In the passenger car fleet, adding production-weighting increases the influence of the mass of vehicles at and below the 0.025 gpm threshold, though this largely affects the estimated curve’s intercept and the impact on the estimated slope is modest. For light trucks, the vehicles with smaller footprints receive more emphasis under production-weighting, while model-weighting increases emphasis for larger pickups. This differential effect is caused by the relatively large number of pickup truck variants at the upper end of the footprint range and the relatively higher production volumes of SUVs with smaller footprints. These attributes of the light truck fleet combine to produce a steeper footprint curve under production-weighting than under model-weighting.

Figure 1-1: OLS-Estimated Footprint Curves by Weighting Scheme, MY 2022 Passenger Car Fleet

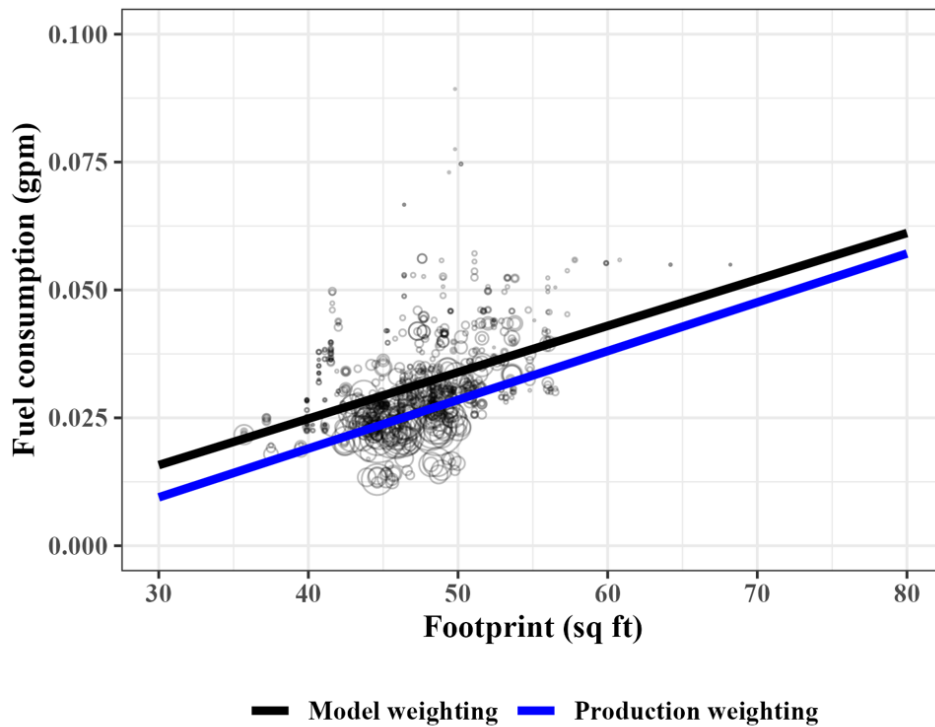
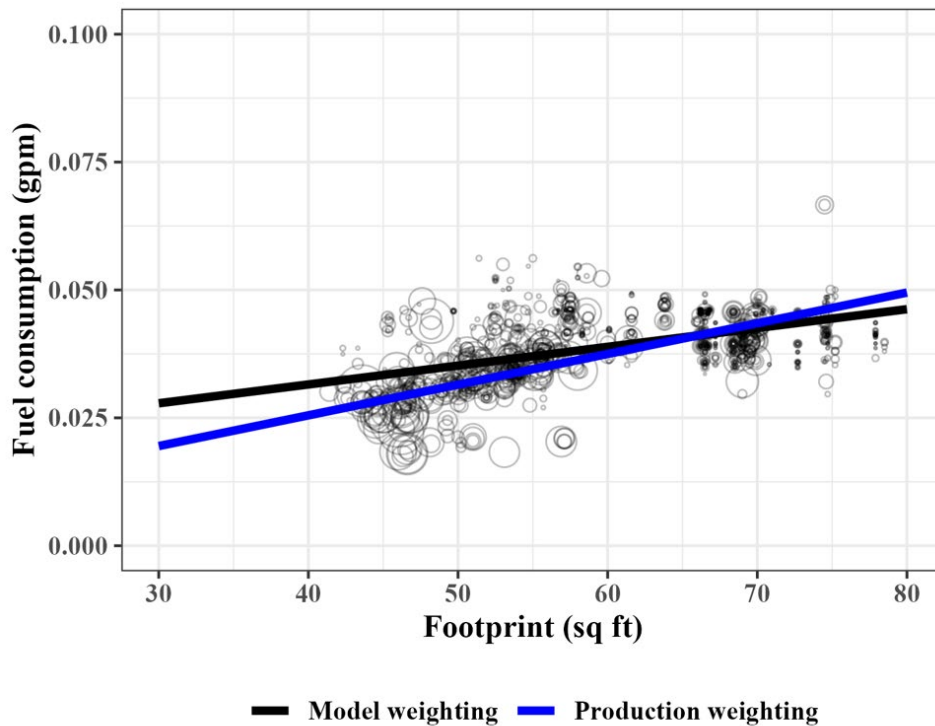


Figure 1-2: Footprint Curves via OLS by Weighting Scheme, MY 2022 Light Truck Fleet



Consistent with the 2012 final rule approach, NHTSA continues to conclude that production-weighting is the more appropriate estimation procedure. The agency is concluding this based on a desire to represent

the on-road fleet best by applying appropriate weights to mass-market vehicles and to avoid placing undue emphasis on a small population of vehicle models that may not be representative of the relationship between fuel consumption and footprint in the broader light-duty fleet.

1.2.3.2.3. *Vehicle Technology Levels*

NHTSA's footprint curve regression analysis considers two versions of the on-road fleet. These data sets capture different approaches to representing the existing fuel consumption-footprint relationship. One reports vehicle fuel consumption values and footprints observed in the current on-road fleet (the "existing technology" dataset) and was assembled from mid-MY 2022 compliance data. The other includes technology application consistent with a projected future fleet where each model would apply the best available technology (the "simulated maximum technology" dataset) based on a simulation using the CAFE Model and a 2022 input fleet. Both datasets exclude diesel, PHEV, BEV, and FCEV vehicle technology.³⁷

The objective of reassessing and potentially updating the footprint curve shapes is to ensure that they are an accurate representation of the fundamental underlying relationship between fuel economy and footprint. Because the agency uses these curves to set standards across multiple years, it is important that the curve specifications are set in a way that captures longer term relationships rather than idiosyncratic or short-term fluctuations in observed fuel economy and footprint levels. Variation in technology application across vehicle models in the observed data could represent short-term technology application choices. For example, if fuel economy technologies are first applied to smaller vehicles and later applied to larger vehicles, the point in the technology adoption cycle at which this analysis is conducted could influence the estimates of the underlying fuel consumption-footprint relationship after the technology has had time to permeate the entire fleet.

Using a simulated fleet that includes wide application of available technologies reduces "noise" (*i.e.*, dispersion in the data) related to transitory market forces. However, a simulated dataset would likely differ from the observed fleet. Further, the resulting technology composition of the fleet derived via simulation depends on the availability and specifications of the technologies in the simulation. In cases where emerging technologies create significant changes in fuel economy but are only applied to a small subset of models in the observed fleet, a simulated fleet can show the potential broader effect of these new technologies. In other cases where observed data include many established and widely applied technologies, using a simulated fleet provides less insight.

To determine the appropriate fleet for the curve fit analysis, NHTSA examines the existing fleet data and the set of emerging fuel-saving technologies. This analysis indicates that most technologies the agency models in its standard-setting analysis that could produce short-term deviations in the footprint curve estimates were applied in a manner that minimized the concerns noted above. For example, while strong hybrid electric vehicle (SHEV) powertrains were excluded from the 2012 final rule's analysis due to the lack of broader application, in 2022, around 8 percent of the gas-powered light truck fleet had SHEV powertrains, which is in line with the rate for the gas-powered fleet as a whole.

1.2.3.2.4. *Controls*

Other vehicle attributes may influence fuel consumption for vehicles of a given footprint. This introduces additional variation in the fuel consumption-footprint relationship, but when variation from these other technologies is correlated with footprint, it can obscure the correlation between these two variables (*i.e.*, it

³⁷ Though these technologies were excluded in the development of the updated footprint curve regression analysis they are still available technologies for the model to select whether it is in the central or EIS analysis.

can introduce statistical bias). For example, manufacturers may employ technologies that improve horsepower (HP), and this may decrease vehicle fuel economy. If HP improvements are more likely to be applied to vehicles with larger footprints than those with smaller footprints, this could bias the slope of the estimated fuel consumption-footprint relationship downward.

In the 2012 final rule analysis, NHTSA considered addressing these concerns by controlling for two factors: the ratio of HP to curb weight (HP/CW) and the ratio of curb weight to footprint (CW/FP). NHTSA estimated a first-stage regression to quantify the effects of having above or below average levels of each attribute on the vehicle's fuel consumption rate. NHTSA then transformed its fuel consumption rate data by adding or subtracting the estimated coefficient for each effect multiplied by the difference between each vehicle's attribute value and the fleetwide average. In that rulemaking, NHTSA ultimately chose to use the control for curb weight to footprint.

For this rule, NHTSA again examines these two factors (HP/CW and CW/FP). The following figures display the effect of applying the two controls on the fuel consumption-footprint correlation, both individually and in combination. Figure 1-3 shows the results of OLS estimation for the passenger car fleet and Figure 1-4 shows similar estimates for the light truck fleet.

The first panel of Figure 1-3 (with no controls) shows a significant number of models with much higher fuel consumption rates than the mass of vehicles sold at similar footprint levels. In the second panel, after controlling for variation in HP/CW, these vehicles exhibit more comparable levels of fuel consumption to other vehicles of similar footprint size (*i.e.*, the dispersion of points is reduced, especially at high fuel consumption levels). Controlling for this variation addresses potential bias in the slope estimate and prevents the agency from assuming a more pronounced relationship between footprint and fuel consumption than is present in the underlying data. NHTSA conducted a similar analysis controlling for CW/FP but found that this metric when included with HP/CW left only minimal variation in fuel consumption to be independently explained by footprint.

Figure 1-3: Passenger Car Footprint Curves with Various Controls

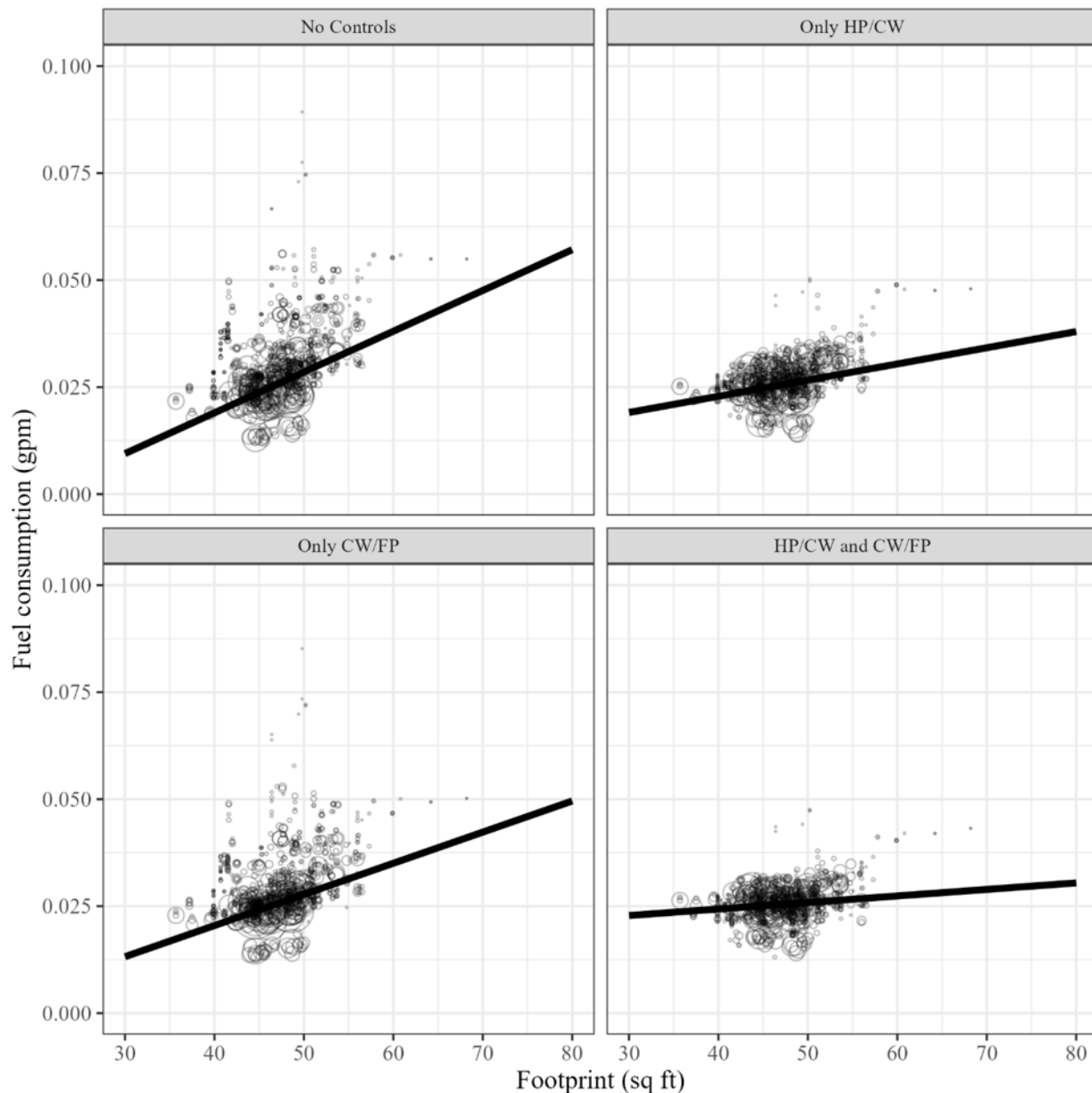
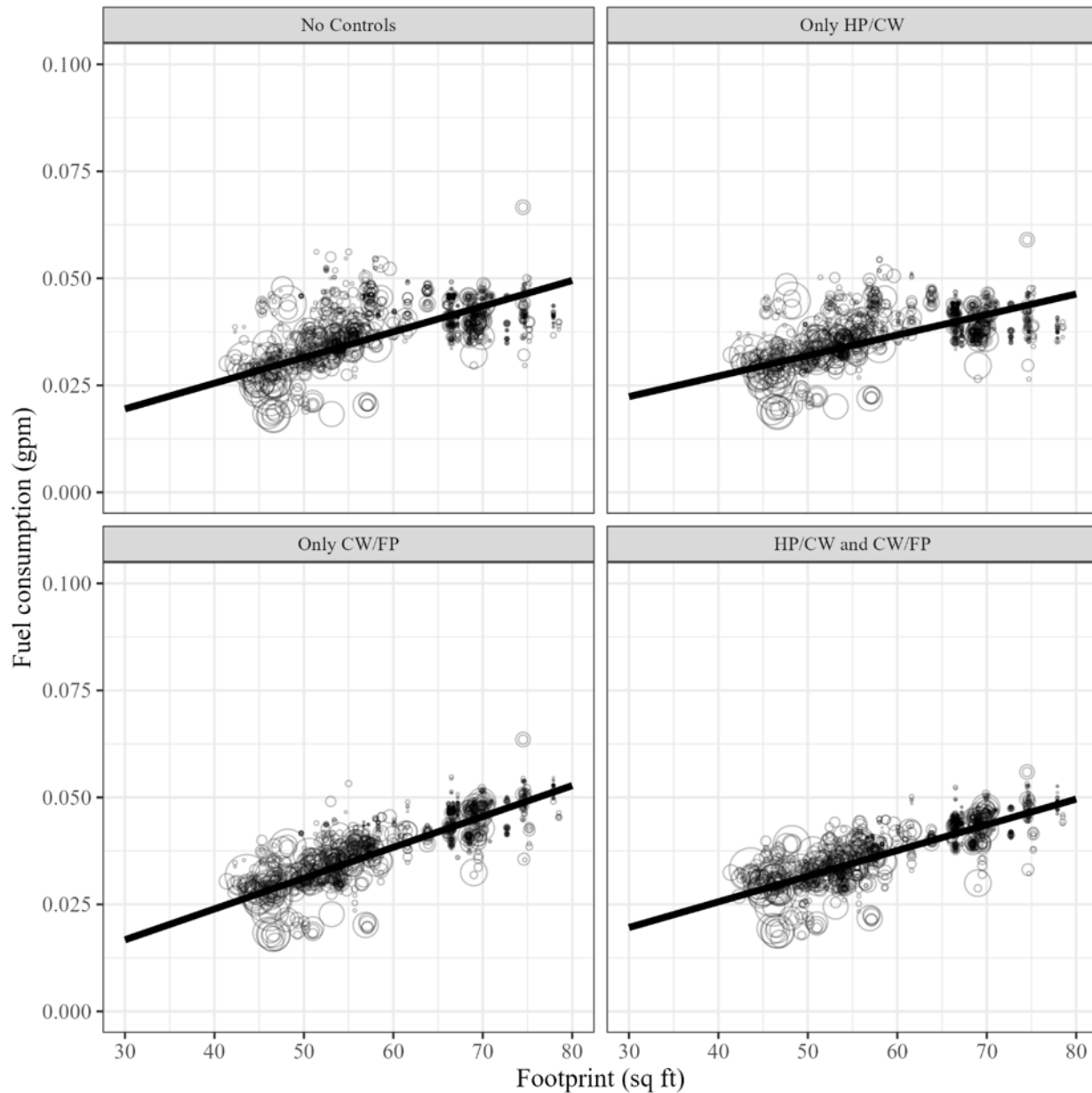


Figure 1-4 displays the same exploration of potential controls as Figure 1-3, but for the light truck fleet. In this fleet, neither measure is perfectly correlated with footprint and therefore each has a meaningful effect in reducing some variation in the analysis.³⁸ Graphically, this can be seen by the reduced dispersion in the datapoints as controls are added. This behavior is caused by the distinct features of SUVs and pickups and the differences between the two in terms of average weight and HP. By adjusting for HP/CW and CW/FP, the fuel consumption of lighter SUVs is adjusted upward closer to the trend, and heavier pickups' fuel consumption is adjusted downward, and similarly moved closer to the general trendline for the data.

³⁸ The adjusted R-squared for the regression is 0.56 with both controls included, while it is only 0.43 without the controls.

NHTSA chose to use only the HP/CW control for passenger cars and chose to control for both HP/CW and CW/FP for light trucks. NHTSA employs this strategy for both its early year and later year analysis.

Figure 1-4: Light Truck Footprint Curves with Various Controls



1.2.3.2.5. *Effect of Fleet Reclassification*

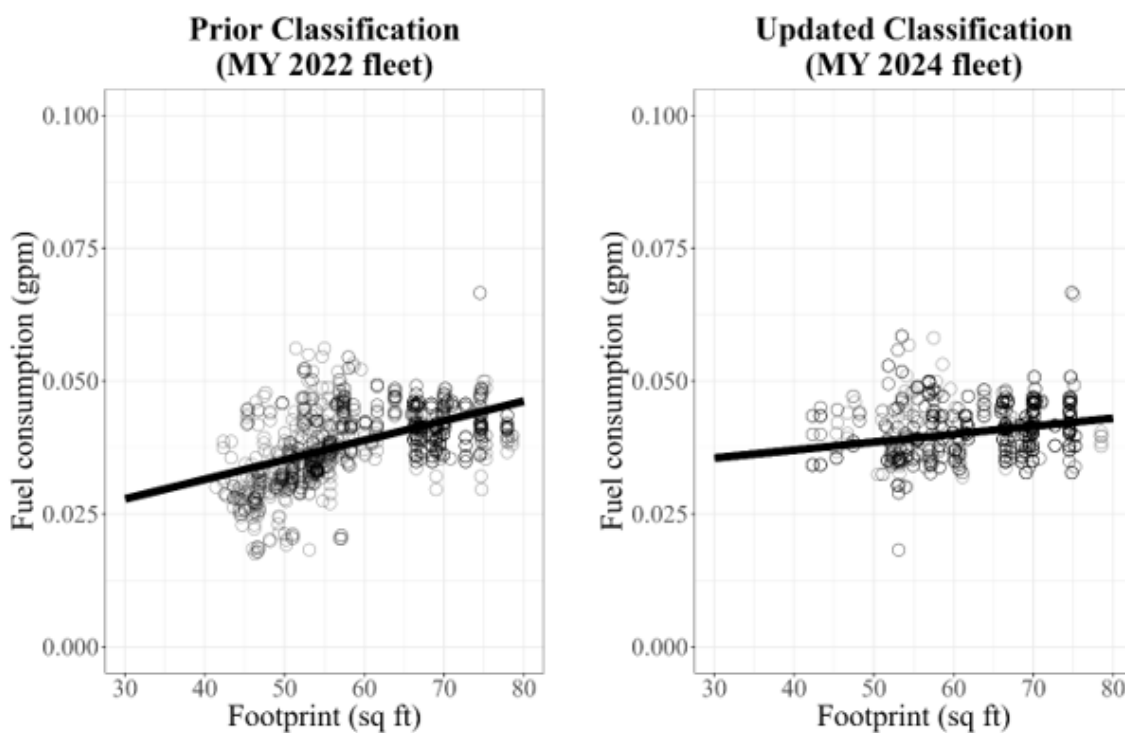
This final rule includes a significant revision to the definition of non-passenger automobiles (or “light trucks”).³⁹ Beginning in MY 2030, this change will move some vehicle models currently classified as non-passenger automobiles to the passenger automobile regulatory class. These “reclassified” vehicles are predominantly SUVs that tend to have higher FE and smaller footprints compared to pickup trucks or other vehicles produced with primarily non-passenger carrying capabilities. As a result, reclassification has the potential to change the observed relationship between footprint and fuel consumption for each

³⁹ See Chapter 2.7 for details.

regulatory class. To investigate this potential effect, NHTSA estimates footprint curve parameters using data from the MY 2024 fleet with vehicles reclassified based on the updated definitions. This has a substantial effect on the light truck fleet’s curve shape, as seen in Figure 1-5.

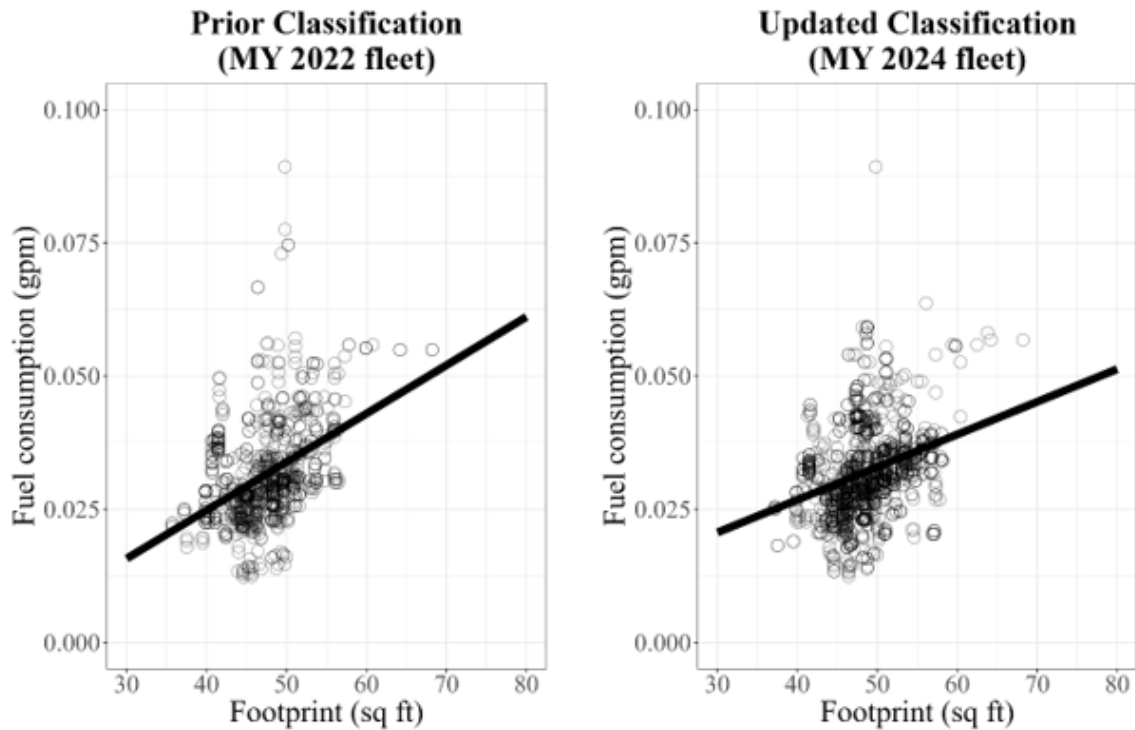
As shown in Figure 1-5, under the updated definitions, many small SUVs would be shifted from the non-passenger automobile to the passenger automobile class. By removing these vehicles from the lower left section of the distribution, the slope of the linear fit becomes greater (*i.e.*, the curve becomes steeper). In this plot, each point is of equal size; however, SUV sales volumes are significantly larger than pickup volumes. Therefore, using production weighting exacerbates the differences shown in Figure 1-5 and produces an even greater divergence between the fit under the prior regulatory class definitions and the fit under the updated regulatory class definitions.

Figure 1-5: Effect of Reclassification on Footprint Curves, Light Trucks



The vehicles reclassified into the passenger car fleet more closely resemble the current existing group of vehicles in this class. Figure 1-6 demonstrates the effect this has on the footprint curve. Adding reclassified vehicles to the passenger car fleet (vehicles, mostly SUVs, which were formerly classified as light trucks) increases the number of observations in the figure but does not alter the distribution of models substantially. Compared to the light truck case, the reclassified vehicles more closely resemble the existing passenger car fleet along the dimensions of fuel consumption and footprint. However, the high production volumes of some reclassified vehicles produce an increase in the slope of the fitted curves relative to the 2022 fleet. This leads to a more significant difference between the estimated coefficients following reclassification.

Figure 1-6: Effect of Reclassification on Footprint Curves, Passenger Cars



Because this analysis demonstrates that using a reclassified fleet would alter the estimates of the footprint curves for both fleets, NHTSA decided it would be appropriate to estimate footprint curves of two vintages for this final rule: one using the current regulatory class definitions (to form the basis of MYs 2022-2029 standards), and a second using the finalized, updated regulatory class definitions (to form the basis of MYs 2030-2031 standards). Both vintages rely on the same approaches regarding regression type, datapoint weighting, vehicle technology levels, and controls. The footprint curves for MYs 2030-2031 are based on the reclassified MY 2024 fleet. NHTSA chose this fleet rather than the MY 2022 fleet because data collected for the MY 2022 fleet omitted some metrics that are necessary for determining the classification of vehicles under the new classification methodology.⁴⁰ Chapter 2.7, FRIA Chapters 6.2 and 8, and preamble Section VI contain detailed discussion of NHTSA’s finalized classification methodology.

1.2.4. Updates to the Existing Footprint Curves

Based on the factors discussed in the preceding sections, NHTSA estimates updated footprint curves with the specification described in Table 1-3.

Table 1-3: Footprint Curve Specifications

Regulatory Class	Regression Type	Datapoint Weighting	Vehicle Technology Levels	Controls
Passenger Car	OLS	Production weights	Existing fleet	HP/CW
Light Truck	OLS	Production weights	Existing fleet	HP/CW and CW/FP

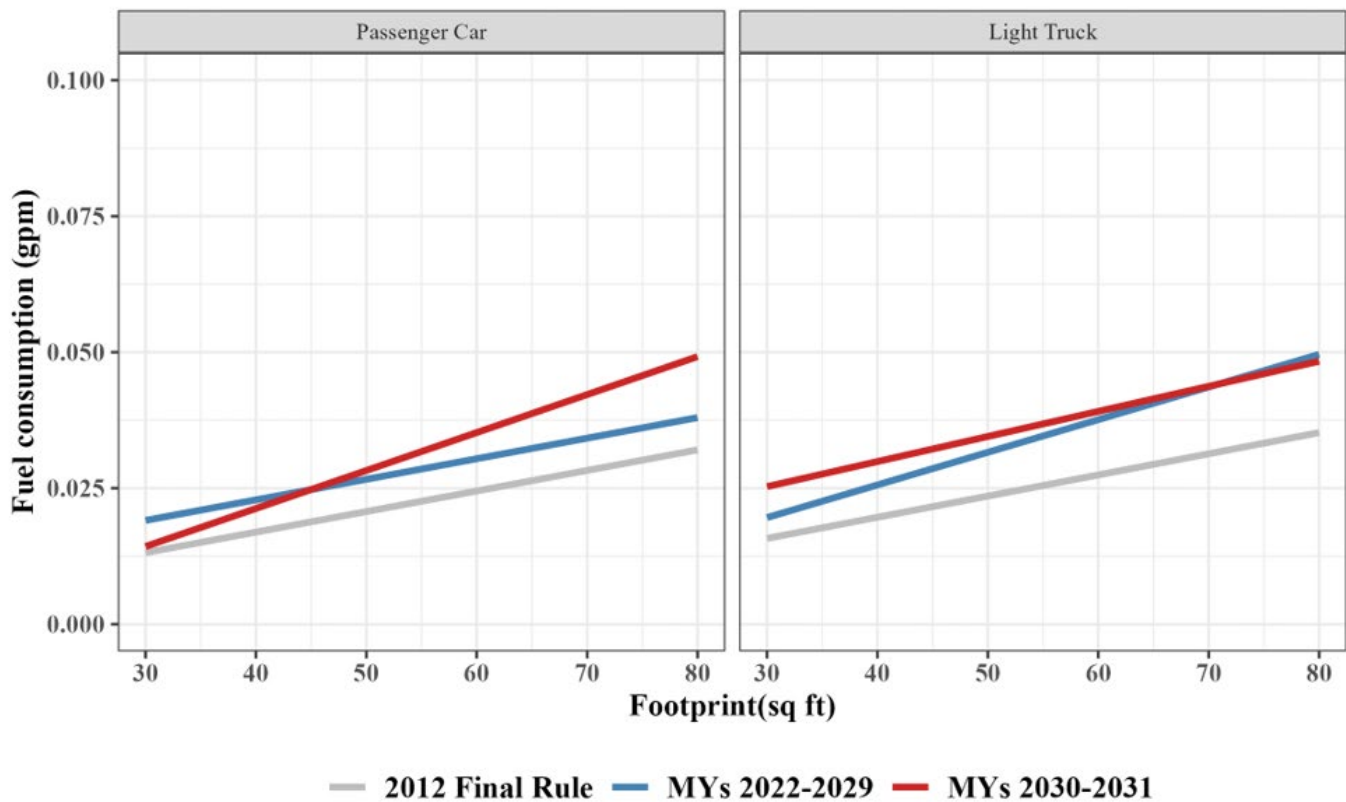
⁴⁰ 49 CFR 537.3 requirements for standardized templates for manufacturer reports were introduced for MY 2023.

Table 1-4 reports the slopes and intercepts of the OLS lines using the footprint curve specifications above for the classified and reclassified fleet as well as the footprint curves derived in the 2012 final rule. Figure 1-7 plots the corresponding curve fits.

Table 1-4: Footprint Curve Estimates

	MY 2008 Simulated Fleet (2012 Final Rule)	MY 2008 On-road Fleet	MY 2022 On-road Feet (MYs 2022-2029, Finalized)	MY 2024 Reclassified Fleet (MYs 2030-2031, Finalized)
Passenger Car				
Slope	0.000378	0.000984	0.000378	0.000698
Intercept	0.00181	-0.01144	0.00774	-0.00665
Light Truck				
Slope	0.000389	0.000669	0.000600	0.000461
Intercept	0.00401	0.00849	0.001602	0.01146

Figure 1-7: Estimated Footprint Curves by Regulatory Class



In most cases, the updated slopes differ from those of prior rulemakings, and this has implications for the standards. A steeper slope relaxes the stringency of targets for larger vehicles relative to those for smaller vehicles, thereby shifting relative compliance burdens among manufacturers based on their respective product mix. A shallower slope tightens the differences in stringency for larger vehicles relative to smaller vehicles.

The updated passenger car slope for MY 2022 yields an estimate equivalent to the passenger car slope used in the 2012 final rule. This does not reflect an equivalent fleet, as the 2012 final rule used simulated rather than observed data and different control variables. Comparing the MY 2008 on-road fleet to the MY 2022 on-road fleet, Table 1-4 shows the decrease in the estimated passenger car slope over time. Under reclassification, the estimated slope lies between the two, likely reflecting the influence of less fuel-efficient SUVs with higher footprint values entering the fleet. In the case of light trucks, the estimated slope in MY 2022 is steeper than the estimate from MY 2008 but like the estimate using the comparable MY 2008 on-road fleet data. As noted in the section above, after reclassification, the light truck fleet slope decreases, though it remains steeper than the simulated MY 2008 estimate.

1.2.5. Cutpoints

The slope and intercept measurements specify a linear function of fuel consumption and vehicle footprint that increases across all footprint levels. In the 2010 final rule, NHTSA determined that this form of the standard only is applied between upper and lower bound footprint levels, or constraints. Outside these constraints, the standard would be flat. NHTSA refers to these constraints as the “cutpoints” of the footprint curve. As with the slope and intercept calculations, NHTSA uses multiple datasets to derive the cutpoints: cutpoints for MYs 2022-2026 came from analyses of the MY 2022 fleet and cutpoints for MYs 2027-2031 came from a MY 2024 fleet with reclassification. NHTSA investigates cutpoint placement by observing the points at which the OLS regression and locally estimated scatterplot smoothing (LOESS)⁴¹ regression lines diverge, indicating a divorce from the consistent linear footprint and fuel consumption relationship. NHTSA investigates these points of divergence further by examining vehicles around the specified cutpoints. The agency selects cutpoints that ensure reasonable segmentation at each point (*i.e.*, avoiding cutpoints that occur at slight variances in a single vehicle model).⁴²

Table 1-5 presents the finalized cutpoints. Figure 1-8 and Figure 1-9 present results of the OLS and LOESS estimation used to determine cutpoint placement.

Table 1-5: Finalized Cutpoints by Regulatory Class and Model Year, in Square Feet

	Passenger Car		Light Truck	
	Lower cutpoint	Upper cutpoint	Lower cutpoint	Upper cutpoint
MYs 2022-2029	43	54	42	74
MYs 2030-2031 (reclassified)	46	56	52	74

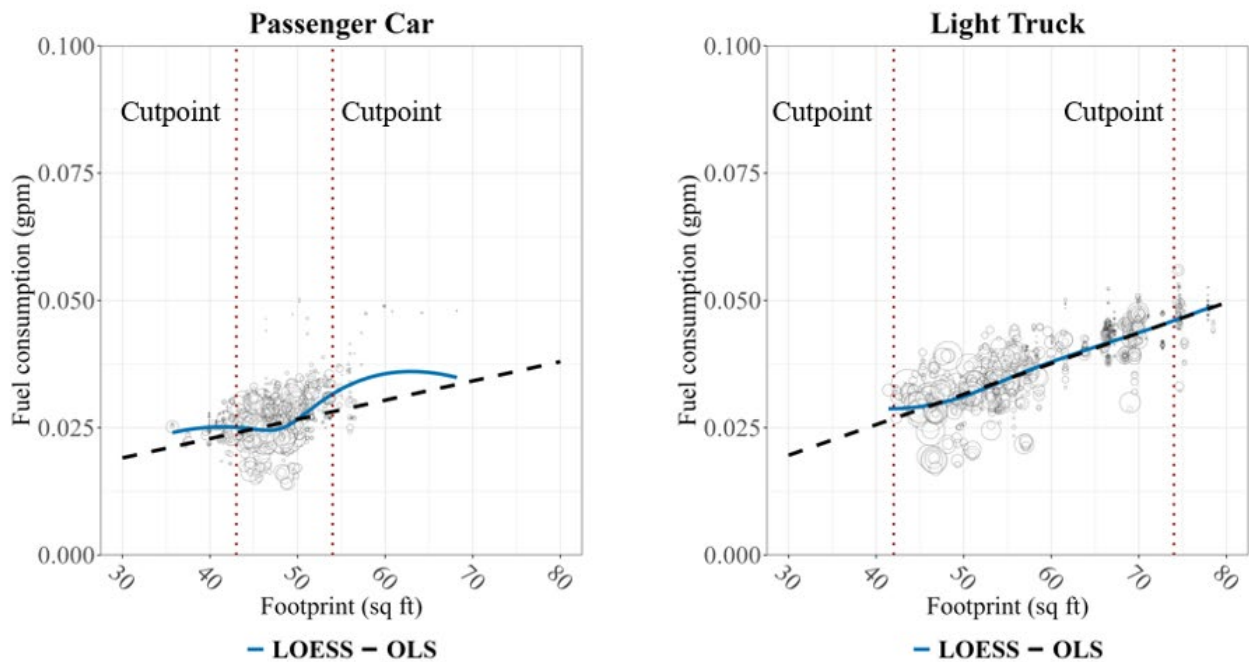
The difference in LOESS fits and OLS fits is easier to observe in the passenger car fleet. The agency cuts off the sloped portion of the light truck function at 42 sq ft (pre-reclassification). Currently, there are not any light trucks offered below 41 square feet. This final cutpoint placement strikes a balance between encouraging manufacturers to introduce new small vehicle models in the United States and discouraging manufacturers from downsizing small vehicles.

⁴¹ LOESS is a form of locally weighted polynomial regression. As applied to the footprint curve analysis, LOESS estimates the relationship between variables locally around a given footprint level, or within nearby levels of footprint. As a result, the estimated slope will vary across different levels of footprint. This contrasts with estimation under OLS, which estimates the relationship across all footprints (*i.e.*, the estimated slope is identical across all footprints). For more information, see Cleveland, W.S. *et al.*, Local regression models (Chapter 8), Statistical Models in S, edited by Chambers, J. M., & Hastie, T. J., First Edition, Wadsworth & Brooks/Cole: Boston, MA (1992), available at: <https://www.taylorfrancis.com/chapters/edit/10.1201/9780203738535-8/local-regression-models-william-cleveland-eric-grosse-william-shyu> (accessed: May 18, 2026).

⁴² Engine or transmission differences in one vehicle model are not considered a slight variance.

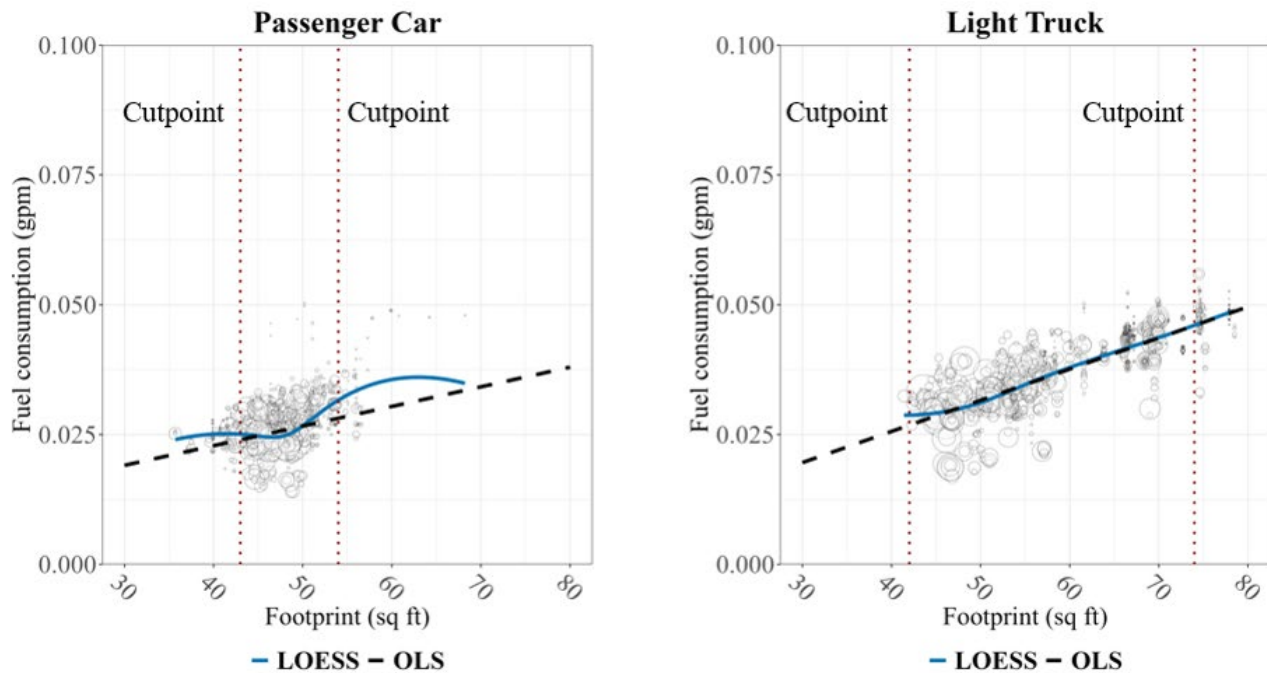
For the upper cutpoint for light trucks, the agency observes that a relatively small portion of the overall fleet exists above 70 square feet. However, these vehicles represent a non-trivial portion of sales for some manufacturers. The light trucks with the largest footprints have significant load-carrying and towing capabilities that make it challenging for manufacturers to add fuel economy-improving technologies yet maintaining these capabilities. The agency believes there is minimal behavioral risk from upper cutpoint placement in this case, as manufacturers are unlikely to increase the size of light trucks that are already at the upper end of marketable vehicle sizes. The high production costs of these vehicles also make it unlikely that the sales of vehicles in this footprint range will increase in response to cutpoint changes.

Figure 1-8: OLS and LOESS Footprint Curve Fits for MY 2022 Fleet Data, by Regulatory Class



In the reclassified MY 2024 fleet, reclassification has limited effect on the cutpoints for passenger cars. As described above, SUVs that move from the light truck fleet to the passenger car fleet fall within a footprint range like the passenger car fleet before reclassification. Hence, the reclassified cutpoints do not differ dramatically from those in the MY 2022 fleet. There is more movement in the reclassified light truck fleet, where the removal of many SUVs eliminates vehicles with relatively small footprints. This causes the LOESS line to deviate from the OLS line at a higher footprint and increases the finalized cutpoint in the light truck fleet from 42 to 52 square feet. Ultimately, NHTSA did not change the upper cutpoint from 74 square feet, as the presence of some larger pickup trucks in the MY 2024 fleet remains post-reclassification. These vehicles create a deviation between the LOESS and OLS fits above 70 sq ft, which NHTSA considered using as the upper cutpoint in the proposal. However, for the reasons mentioned above, the light trucks with these large footprints have significant load-carrying and towing capabilities, and adding fuel-saving technologies makes it particularly challenging in a way that fully maintains these capabilities. The agency applies similar logic to create cutpoints for the MY 2022 fleet to the upper cutpoint selection for the reclassified MY 2024 fleet.

Figure 1-9: OLS and LOESS Footprint Curve Fits for Reclassified MY 2024 Fleet Data, by Regulatory Class



1.2.6. Rescaling

The estimated footprint curves and cutpoints form the basis for the regulatory alternatives in each of the model years NHTSA is considering in this rulemaking. The estimated slopes, intercepts, and cutpoints presented above describe a single target function or stringency. These parameters are adjusted, or “rescaled,” to define different stringency levels. NHTSA uses a multiplicative rescaling approach, defined below.

NHTSA determines the upper and lower fuel economy bounds based on the selected cutpoints and estimated slope and intercept. The agency first calculates the value of the estimated linear function that maps footprint to fuel consumption rate (in gpm) at the two function cutpoints. The reciprocals of these values are the initial upper and lower bound parameters a_0 and b_0 . Equation 1-4 shows how these values are determined based on the estimated slope c_0 and estimated intercept d_0 :

Equation 1-4: Initial Determination of Upper and Lower Constraint Values

$$a_0 = \frac{1}{c_0 \times \text{UpperCutpoint} + d_0}; b_0 = \frac{1}{c_0 \times \text{LowerCutpoint} + d_0}$$

NHTSA rescales in the fuel consumption space. The agency rescales the parameters and the initial value of the slope and intercept by multiplying each parameter by a constant, k (the “scaling factor”). Because parameters a and b are in fuel economy units mpg), they are scaled by the reciprocal of k . The footprint curves, however, are specified in fuel consumption (gpm) and are therefore multiplied directly by the scaling factor. This process is described in Equation 1-5.

Equation 1-5: Scaling Equations for Constrained Linear Function Parameters

$$a_k = \frac{1}{k} \times a_0$$

$$b_k = \frac{1}{k} \times b_0$$

$$c_k = k \times c_0$$

$$d_k = k \times d_0$$

NHTSA follows the process described in this chapter to develop the coefficients for each regulatory alternative. NHTSA's approach to developing the regulatory alternatives is described in greater detail in FRIA Chapter 3 and preamble Section III.

2. What Inputs Does the Compliance Analysis Require?

NHTSA uses the CAFE Compliance and Effects Modeling System (the CAFE Model or the Model) to simulate manufacturers’ potential responses to new CAFE standards and to estimate various impacts of those responses. The Volpe National Transportation Systems Center (Volpe or the Volpe Center) of DOT develops, maintains, and applies the Model for NHTSA. NHTSA has used the CAFE Model to perform analyses supporting every CAFE rulemaking since 2001.

The CAFE Model simulates the possible effects of standards on society and manufacturers. The Model accomplishes this by first simulating the actions industry may take to comply with a set of standards, and second, calculating the resulting societal costs and benefits caused by those actions. In addition, the CAFE Model applies various technologies to different vehicle models in each manufacturer’s product line to simulate how each manufacturer might progress toward compliance with a 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 added technological cost related to a change in achieved average fuel economy, and, if applicable, CAFE-related civil penalties that may result.⁴³ For a given manufacturer, the compliance simulation algorithm applies technologies either until the manufacturer runs out of cost-effective technologies, or until the manufacturer exhausts all available technologies available during a refresh or redesign cycle within the regulatory timeframe.⁴⁴ 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—though the Model reflects that no civil penalties will be required to be paid for the analysis period. This compliance simulation process is repeated for each model year of both the rulemaking timeframe and study period that runs through MY 2050. For model years after the standard-setting period, the Model assumes the standards remain constant from the last year of the standard-setting period through MY 2050. The Model can continue to apply technology if a manufacturer is either not meeting the standard or if the technology costs can be recouped within the payback period.

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.

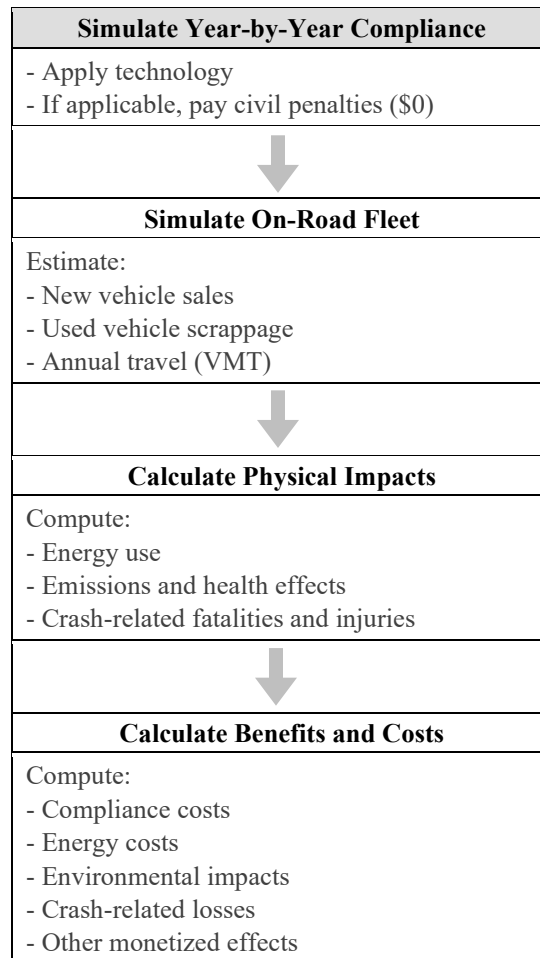
- CAFE Model Documentation
- CAFE Model Input File
- Parameters Input File
- Technologies Input File
- Scenarios Input File
- CAFE Model Executable File
- Market Data Input File
- CAFE Analysis Autonomie Documentation
- Autonomie Input and Assumptions Description Files
- CAFE Model Output File
- Argonne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

⁴³ NHTSA recognizes, and the CAFE Model reflects, that Pub. L. No. 119-21, commonly known as “One Big Beautiful Bill Act,” (OB3) reduces the civil penalties for violations of NHTSA’s CAFE standards to \$0 as of the date of enactment of the statute, for those model years for which NHTSA has not issued notices of non-compliance (specifically, MY 2022 and beyond).

⁴⁴ See Section VI of the preamble describing changes related to civil penalties being \$0, and how NHTSA modeled all manufacturers as not willing to pay fines.

The basic design of the CAFE Model is as follows: the system first simulates 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 other economic externalities. In a highly summarized form, Figure 2-1 shows the basic categories of CAFE Model procedures, and the sequential flow between different stages of the modeling. Figure 2-1 does not present specific model inputs or outputs or most of the specific procedures and model interactions. The CAFE Model documentation accompanying this Final TSD presents these details.

Figure 2-1: CAFE Model Procedures and Logical Flow



When 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 representation of the registered light-duty vehicle (LDV) population in the United States for each model year and calendar year (CY). The CAFE Model then generates estimates for this fleet of the following (for each MY and CY included in the analysis): lifetime travel, fuel consumption, 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). The Model then uses these estimates to calculate the benefits and costs associated with each regulatory alternative relative to a No-Action Alternative.

To perform these analyses, 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 Volpe. In addition, some of the input data come from modeling and simulation analysis

performed by experts at Argonne National Laboratory (Argonne) using their Autonomie full-vehicle simulation model and Battery Manufacturing Cost Estimation (BatPaC) battery cost model.⁴⁵ 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, which is, in itself, a third example of an estimate used). Other inputs are derived from other models, such as fuel price projections from the U.S. Energy Information Administration (EIA), Argonne’s fuel-cycle emissions analysis model, the vehicle emissions analysis model of the EPA, and engine models from Ingenieurgesellschaft Auto und Verkehr (IAV) and Southwest Research Institute (SwRI).

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 simulate manufacturers’ decisions, and their effectiveness and cost. The inputs and analyses for the effects calculations, including economic, safety, and environmental effects, are discussed later in Chapters 4 through 7, though the overview of inputs below provides a brief description of the information contained in the input files that support those calculations. Throughout these chapters, NHTSA will occasionally use DOT to refer to the collaborative work performed by both NHTSA and Volpe, because both organizations are part of DOT.

2.1. Overview of Analysis Inputs and Assumptions

The CAFE Model is 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 automobile and non-passenger automobile regulatory classes, and stringency of the CAFE standards for each model year to be analyzed. In addition, 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 among 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 initial forecast of the vehicle models offered for sale during the simulation period.⁴⁶ The compliance simulation then attempts to bring each manufacturer into compliance with the

⁴⁵ For details on how Autonomie full-vehicle model simulations were used in this rulemaking, see Chapter 2.4

⁴⁶ The DOT-developed Market Data Input File that contains the forecast used for this final rule is available at <https://www.nhtsa.gov/corporate-average-fuel-economy/cafe-compliance-and-effects-modeling-system>. However, the CAFE Model is publicly available and interested persons could develop their own initial forecasts to feed into the Model to run.

applicable standards defined by the regulatory scenario contained within an input file developed by the user.⁴⁷

Estimating impacts involves calculating resultant changes in new vehicle costs, estimating a variety of costs (e.g., fuel cost) and effects (e.g., increased or decreased road congestion) occurring as vehicles are driven over their lifetimes before eventually being scrapped, and estimating the monetary value of these effects. Estimating impacts also involve consideration of consumer responses (e.g., the impact of vehicle fuel economy, operating costs, and vehicle price on consumer demand for passenger automobiles and non-passenger automobiles). 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 Motor Vehicle Emissions Simulator (MOVES) model developed by EPA to estimate “vehicle” or “downstream” emission factors (EFs) for criteria pollutants,⁴⁸ and uses four U.S. Department of Energy (DOE) and DOE-sponsored models to develop inputs to the CAFE Model, including three developed and maintained by DOE’s Argonne National Laboratory. The agency uses the National Energy Modeling System (NEMS) developed by EIA to estimate fuel prices,⁴⁹ uses the Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET) model, created by Argonne, to estimate emissions rates from fuel production and distribution processes,⁵⁰ and uses Argonne’s BatPaC tool to estimate hybrid vehicle battery costs.⁵¹ NHTSA also sponsored DOE/Argonne to run Autonomie full-vehicle modeling and simulation system to estimate the fuel economy impacts for over a million combinations of technologies and vehicle types.⁵² Other chapters in this Final TSD and discussion in the accompanying FRIA describe details of the agency’s use of these models. In addition, as discussed in the Final SEIS accompanying this final rule, DOT relies on a range of climate models to describe impacts on energy, air quality, and non-criteria emissions. The Final SEIS 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 NHTSA’s analysis, and that, in turn, provide model results underlying the central analysis as well as the Final SEIS accompanying this final rule.

⁴⁷ Scenarios can be altered or added using the Scenarios Input File discussed below in Chapter 2.1.5 and in the CAFE Model Documentation.

⁴⁸ See EPA, MOVES and Mobile Source Emissions Research, last revised: Sept. 18, 2025, available at: <https://www.epa.gov/moves> (accessed: May 25, 2026). This final rule uses version MOVES5, available at <https://www.epa.gov/moves/latest-version-motor-vehicle-emission-simulator-moves>.

⁴⁹ See EIA, Annual Energy Outlook 2025: Download the National Energy Modeling Systems (NEMS), last revised: Apr. 15, 2025, available at: https://www.eia.gov/outlooks/aeo/info_nems_archive.php (accessed: May 25, 2026). This final rule uses fuel prices estimated using the Annual Energy Outlook (AEO) 2025 version of NEMS. See EIA, Annual Energy Outlook 2025, last revised: Apr. 15, 2025, available at: <https://www.eia.gov/outlooks/aeo> (accessed: May 25, 2026).

⁵⁰ Information regarding GREET is available at <https://greet.es.anl.gov>. This final rule uses the 2024 version of GREET.

⁵¹ Argonne National Laboratory, BatPaC: Battery Manufacturing Cost Estimation, available at: <https://www.anl.gov/partnerships/batpac-battery-manufacturing-cost-estimation> (accessed: May 25, 2026).

⁵² 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 hybridization. Information regarding Argonne’s BatPaC model is available at <https://www.anl.gov/cse/electrochemical-chemical-TEA>. In addition, the impact of engine technologies on fuel consumption, torque, and other metrics was characterized using GT-POWER simulation modeling in combination with other engine modeling that was that was conducted by IAV Automotive Engineering, Inc. and 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>.

The CAFE Model Input File is used to define the analysis fleet,⁵³ the characteristics of the fuel-saving technologies considered in the analysis, safety considerations, and major economic factors. The input files contain about 150,000 records and data points, all considered in the CAFE Model. The purpose and use of many of the Model inputs remain unchanged relative to previous versions of the CAFE Model. However, DOT staff continuously update the values of the inputs to represent the latest information available.

The CAFE Model documentation accompanying this final rule lists all the inputs, defines them, and describes how the Model uses the inputs.⁵⁴ However, this subsection provides an overview of the various CAFE Model Input File, their general purpose, and a brief description of the data they contain. Like the CAFE Model documentation, this subsection is organized based on CAFE Model input types.

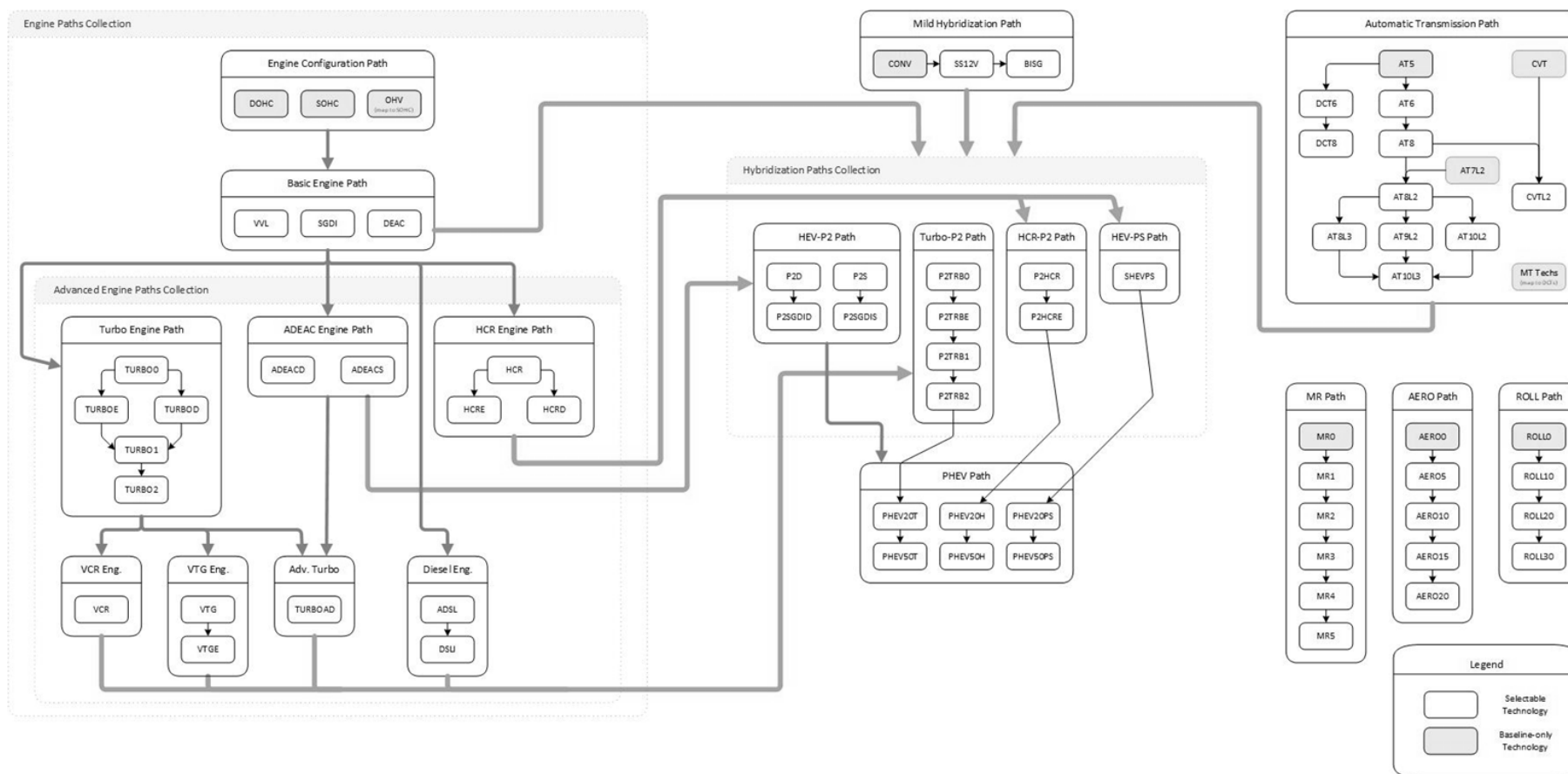
2.1.1. Technology Options and Pathways

NHTSA defines the technology options available for the CAFE Model analysis and groups those options into pathways. The pathways define relations of mutual exclusivity between conflicting sets of technologies. In addition, each path designates the direction in which vehicles are allowed to advance as the modeling system evaluates specific technologies for application. Figure 2-2 shows the technology options and pathways used in the analysis.

⁵³ Discussed further below, the “analysis fleet” or “baseline fleet” (used interchangeably) located in the “Vehicles” worksheet of the Market Data Input File is NHTSA’s 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 model years, depending on data availability.

⁵⁴ CAFE Model Documentation <https://www.nhtsa.gov/corporate-average-fuel-economy/cafe-compliance-and-effects-modeling-system>.

Figure 2-2: CAFE Model Technology Pathways



PHEV path considered in charge sustaining mode only for standard setting analysis.

Table 2-2 in Chapter 2.2.1.3 lists the technology options available for the Light Duty Vehicle (LDV) analysis.

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 based on MY 2024 mid-model year compliance data. The file also contains a range of other inputs specific to individual manufacturers but not to individual vehicle models.

The file contains a set of worksheets, as follows:

- **“Manufacturers” worksheet:** Lists specific manufacturers; indicates preference for manufacturers to pay CAFE penalties over applying technologies that would not be cost effective (the Model recognizes that no penalties would be paid during the analysis period)⁵⁵ and indicates what “payback period” defines buyers’ willingness to pay (WTP) for fuel economy improvements.
- **“Credits and Adjustments” worksheet:** Enumerates estimates of credit and adjustment values available in the CAFE program—except CAFE credits, which are credits that manufacturers earn for exceeding their applicable CAFE standards.⁵⁶ The credits and adjustments in this worksheet (specified in units of carbon dioxide (CO₂)) grams per mile, except for Flex Fuel Vehicle (FFV) credits which are in mpg) are divided into sections by type and are specific to each manufacturer, regulatory category, and model year.⁵⁷ The data are divided vertically by manufacturer and type of credit/adjustment and divided horizontally by regulatory class and model year. As discussed in Chapter 3.7, the AC efficiency and OC adjustment values in this worksheet are the values NHTSA estimates to be achievable for each manufacturer. 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.⁵⁸ See Section II of the preamble for further discussion on how AC efficiency and OC technologies have been incorporated into the CAFE analysis.
- **“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; 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. New for this rulemaking, the vehicle tab includes additional regulatory class information to support analysis of the changes to vehicle classification that go into effect starting for MY 2030. As a result of the changes to the criteria for non-passenger automobiles, some vehicles are expected to switch to being classified as passenger

⁵⁵ For this analysis NHTSA assumes that all manufacturers will attempt to meet their applicable CAFE standards with a maximum practicable effort.

⁵⁶ CAFE credit banks can be found in the “Manufacturers” worksheet in the Market Data Input File.

⁵⁷ FFV credits are just a place holder within the credits and adjustments worksheet and are not longer tracked or used in this analysis.

⁵⁸ For more discussion on how the CAFE Model incorporates off-cycle technologies into its compliance simulation, see Chapter 2 S5.4 of the CAFE Model Documentation.

automobiles during the standard-setting timeframe. Additional information on vehicle reclassification can be found in Chapter 2.7 of the Final TSD and Section VI of the preamble.

- **“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.
- **“Engines” worksheet:** Identifies specific engines used by each manufacturer, and for each engine lists a unique code (used for identifying which engine is used for each vehicle model configuration); identifies the fuel(s) with which the engine is compatible; specifies the valvetrain design (*e.g.*, dual-overhead camshaft [DOHC]); specifies the engine’s displacement, cylinder configuration and count; identifies the engine’s aspiration type (*e.g.*, naturally aspirated or 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:** Identifies specific transmissions used by each manufacturer and for each transmission; lists a unique code (which is used for identifying which transmission is used 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:** Separate from 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, this worksheet specifies the share of the entire fleet to which the technology may be applied in each model year.
- **“Technology Class” worksheets:** In a separate worksheet for each of the 10 technology classes (discussed below), these worksheets identify whether and how soon the technology is expected to be available for wide commercialization; specify the percentage of miles a vehicle is expected to travel on a secondary fuel (if applicable, as for PHEVs); indicate a vehicle’s expected electric power and all-electric range (AER) (if applicable); specify expected impacts on vehicle weight; specify estimates of costs for technologies in each model year (and factors by which hybrid vehicle battery costs are expected to be reduced in each model year); specify any estimates of maintenance and repair cost impacts; and specify any estimates of consumers’ WTP for the technology.
- **“Engine Technology Class” worksheets:** In a separate worksheet for each of the 31 initial engine types, these worksheets, which can be identified by the number of cylinders, number of cylinder

banks, and configuration (dual overhead valve [DOHC], unless identified as overhead valve [OHV] or single overhead cam [SOHC]) in the name of the worksheet, specify 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, and the following are used in the standard-setting analysis:

- **“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), 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 refueling event, the share of the tank refueled during an average refueling event, the value of travel time (in dollars per hour per vehicle), 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).
- **“Vehicle Age Data” worksheet:** Specifies nominal average survival rates and annual mileage accumulation for cars, vans and SUVs, and pickup trucks. These inputs are used only for displaying estimates of avoided fuel savings 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 passenger automobiles and non-passenger automobiles in the total U.S. market for new vehicles. This worksheet also includes an annual forecast of passenger automobile 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 LDVs sold in each model year of the analysis period.
- **“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 MY 2024), and separately for cars, vans and SUVs, and pickup trucks, specifies the initial size (*i.e.*, number of new vehicles produced for sale in the United States) of the fleet, the number still in service in the indicated calendar year (here, CY 2024), the relative shares of different fuel types, the average fuel economy achieved by vehicles with different fuel types, and the averages of 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, it specifies the values assigned to preventing highway fatalities, non-fatal 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 MYs 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 MY 2024 are defined to have age=0 in CY 2024, and to have reached age=10 in CY 2034.
- **“Employment Values” worksheet:** Specifies the estimated average revenue 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 sulfur dioxide (SO_x) 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 nitrogen oxide (NO_x), SO_x, and PM_{2.5} (particulate matter 2.5 microns or less in diameter) emissions, separately for upstream and vehicular emissions, and for each of CYs 2020, 2025, and 2030, specifies estimates of various health impacts, such as premature mortality, acute bronchitis, and respiratory hospital admissions. Consulting with technical staff at EPA and Argonne, 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 vehicle emissions.
- **“Criteria Pollutant Emission Costs” worksheet:** Separately for NO_x, SO_x, and PM_{2.5} emissions, separately for upstream and vehicular emissions, and for each of CYs 2020, 2025, and 2030, specifies social costs on a per-ton basis.
- **“Upstream Emissions (UE)” worksheets:** Specifies EFs (in grams per million British thermal unit [BTU]) for each included criteria pollutant (*e.g.*, NO_x) and toxic air contaminant (*e.g.*, benzene) separately for gasoline, E85, diesel, electricity, hydrogen, and CNG, separately for domestic and total global sources, separately for CYs 2020, 2025, 2030, 2035, 2040, 2045, and 2050, and separately for various upstream processes (*e.g.*, petroleum refining).
- **“Tailpipe Emissions (TE)” worksheets:** Specifies vehicle-based EFs (in grams per mile) for carbon monoxide, volatile organic compounds (VOC), NO_x, PM_{2.5}, methane (CH₄), N₂O, acetaldehyde, acrolein, benzene, butadiene, formaldehyde, and diesel particulate matter (PM) 10 microns or less in diameter (PM₁₀) separately for gasoline and diesel, for each of MYs 1975-2050, for each vehicle vintage through age 39.
- **“BTW Emissions” worksheet:** Specifies separate brake and tire wear (BTW) emission rates across fuels (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” or “Light Truck”) and each model year. Inputs specify the standards’ functional forms and define CAFE coefficients for each regulatory alternative in each model year. Additional inputs specify minimum CAFE standards for domestic passenger automobile fleets, identify specific model years for which new standards are being finalized, and define unit costs and caps on adjustments generated from AC efficiency and OC technologies.⁵⁹

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. For a complete list and discussion of runtime settings, see the CAFE Model documentation. The settings discussed here include those used in the standard-setting analysis. These include 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); 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. The runtime settings also support a selection of a dynamically computed or a user-defined sales forecast for the No-Action Alternative and support 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, hybrid 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 hybrid battery cost model simulations developed by Argonne. 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.

For a complete list of the databases please see the CAFE Model Documentation. The extracted databases relevant to the standard-setting analysis, 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

⁵⁹ See Chapter 3.7 for additional details on how the CAFE Model simulates AC efficiency and OC technologies.

Input Files. Each estimate is specified as a percentage of the “base” technology combination for the indicated technology class.

- **“Battery_Costs.csv”**: Specific to technology combinations involving vehicle hybridization, defines a database of estimates of corresponding BatPaC-based base year battery direct manufacturing costs (DMC) (before learning effects and RPE adjustments) 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 Argonne using the Autonomie model. Though 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 LD fleet, the workbooks Argonne 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 10 databases that contain the outputs of the Autonomie full-vehicle simulations for the LDV fleet. These 10 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.⁶⁰
- **“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, and component specifications.
- **“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 hybrid electric motor efficiencies. It also contains the inputs, assumptions, and outputs of the hybrid vehicle battery pack modeling performed by Argonne for this analysis.

2.1.9. Where to Find the Internal NHTSA Files

For the purpose of transparency and easier review of the files used for this analysis, NHTSA will post its CAFE Model source code, inputs, and outputs on the NHTSA CAFE Model website located at <https://www.nhtsa.gov/corporate-average-fuel-economy/cafe-compliance-and-effects-modeling-system>.⁶¹

⁶⁰ 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.

⁶¹ Also see NHTSA, Corporate Average Fuel Economy, last revised: 2025, available at: <https://www.nhtsa.gov/laws-regulations/corporate-average-fuel-economy> (accessed: May 25, 2026).

Below is a table of all CAFE Model Files referenced in this Final 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 2-1: Internal NHTSA Files

NHTSA Internal File	File Location
NHTSA CAFE Model Website	https://www.nhtsa.gov/corporate-average-fuel-economy/cafe-compliance-and-effects-modeling-system
CAFE Model Documentation	NHTSA CAFE Model Website > Downloads > Model Documentation
CAFE Model Input File	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > CAFE Model Inputs Zip
Market Data Input File	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > CAFE Model Inputs Zip > market_data_ref.xlsx
Parameters Input File, Standard-Setting Analysis	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > CAFE Model Inputs Zip > parameters_ref.xlsx
Parameters Input File, EIS Analysis	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > CAFE Model Inputs Zip > parameters_EIS.xlsx
Technologies Input File	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > CAFE Model Inputs Zip > input > technologies_ref.xlsx
Scenarios Input File, Standard-Setting Analysis	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > CAFE Model Inputs Zip > scenarios_LD_ref.xlsx
Scenarios Input File, EIS Analysis	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > CAFE Model Inputs Zip > scenarios_LD_EIS.xlsx
CAFE Model Outputs File, Standard-Setting Analysis	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > LD_ref.zip
CAFE Model Outputs File, EIS Analysis	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > LD_EIS.zip
Vehicle Report Output File	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > LD_ref.zip > reports-csv > vehicles_report.xlsx
CAFE Model Compliance Output File	NHTSA CAFE Model Website > Downloads > Central & EIS Analysis > LD_ref.zip > reports-csv > compliance_report.xlsx
CAFE Model Executable File	NHTSA CAFE Model Website > Downloads > Model Software > CAFE Model (installed directory)
CAFE Model Program Directory	
CAFE Model Battery Costs File	
CAFE Model Fuel Economy Adjustment Files	
CAFE Analysis Autonomie Documentation ⁶²	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	

⁶² The Argonne report is titled “Vehicle Simulation Process to Support the Analysis for MY 2027 and Beyond CAFE and MY 2030 and Beyond HDPUV FE Standards.” However, for ease of use and consistency with the Final TSD, it is referred to as “CAFE Analysis Autonomie Documentation.”

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

For a complete discussion on all input options available in the Market Data Input File please see the CAFE Model Documentation. This chapter focuses on the input options used in the standard-setting analysis.

The starting point for the evaluation of different stringency levels for fuel economy standards is the analysis fleet, which is a snapshot of the recent LDV market. For this analysis and supporting rulemaking for MYs 2027-2031, two analysis fleets were constructed to represent the MY 2024 fleet of light-duty vehicles sold. One fleet was constructed for the standard-setting analysis, which excludes BEVs, consistent with 49 U.S.C. 32902(h). The second, which is used for the Final SEIS analysis, includes BEVs. Specifically, the Model’s interface now includes a toggle that restricts the application of certain available technologies in all model years included in the analysis. The 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.⁶³

The “Credits and Adjustments” tab of the Market Data Input File summarizes FCIVs previously claimed by manufacturer, by regulatory class. On this tab, the Market Data Input File includes AC efficiency, OC improvement values, and flexible-fuel Vehicle credits based on manufacturers’ 2024 mid-model year compliance data. For this analysis, manufacturers credit values in this tab are now held constant from years 2024-2050.⁶⁴ For more information on how manufacturers may earn FCIVs for AC and OC technologies under EPA’s regulations for measuring fuel economy, please see Final TSD Chapter 3.7 and preamble Section VI.

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 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 considered 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.

⁶³ The CAFE Model does not generate compliance paths a manufacturer should, must, or will deploy. It is intended 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.

⁶⁴ AC efficiency and OC improvement value caps and cap profiles through the years are now set and controlled in the Scenarios Input File.

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 to ensure vehicle attributes and technologies are captured accurately is key to estimating costs and benefits resulting from different stringencies in NHTSA’s constrained standard-setting analysis. 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 fact 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 Final 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 cannot adequately characterize every potentially relevant nuance of the automotive marketplace. As with every fuel economy rulemaking, the analyses 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 LD analysis, 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 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 Argonne Autonomie simulations for many effectiveness estimates used in the compliance simulation. In these simulations, Argonne projects the fuel economies for 10 different types of light-duty vehicles, 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 hybrid vehicle 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 4-cylinder engine is not projected to be the same as adding DEAC to a naturally aspirated OHV V 8-cylinder engine. Similarly, some naturally aspirated inline 4-cylinder engines may retain four cylinders when turbocharged (“4C1B” engine technology class, meaning an engine with 4 cylinders and 1 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 to a higher output naturally aspirated 4-cylinder when adopting 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. Alternatively, 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 time spent 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 also would 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 hybrid 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 across vehicles 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 mass reduction 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.” Vehicles that share engines codes, and thus engines, will adopt engine technologies together, while vehicles that share transmissions will adopt them together. Likewise, vehicles that share platforms will adopt mass reduction technologies together. Redesign cycles for all 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.

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 include 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 given 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 the available public information. 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 confidential business information (CBI). In these cases, DOT staff rely on best information available, and, occasionally, analyst or engineering judgement, or described analytical techniques, as in the case of mass reduction technology. When manufacturers or suppliers do provide CBI, NHTSA often verifies the information in due time, usually through contracted analysis at independent labs. NHTSA often tries 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 MY 2016 light-duty fleet, and carried these values forward, by nameplate, for the MY 2024 fleet. With this approach, it is possible that DOT underestimates the extent to which manufacturers have added harder-to-observe technologies in the MY 2024 fleet since MY 2016, increasing the risk of “double-counting” effectiveness, especially for aerodynamics and rolling resistance. Though 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. 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.

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 population of the analysis fleet. When

analyst judgement is used, DOT staff try to make clear what underlying data and logic inform 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 mid-MY 2024 compliance data as the basis of the analysis fleet.⁶⁵ For light-duty vehicles, compliance data contains information about projected sales volumes, vehicle fuel economies, and vehicle footprints, and often contains some information about engine architecture, transmission architecture, and vehicle drive configuration. For each vehicle nameplate, DOT staff identified and downloaded manufacturer specification sheets, usually from the manufacturer media website, or from online marketing brochures.⁶⁶ From specification sheets, DOT staff gathered information to identify engine technologies, engine families, transmission technologies, transmission families, and hybrid drivetrain technologies. NHTSA 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 MY 2024 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 to evaluate how competitive positions may evolve as manufacturers add fuel-saving technologies and adjust their product plans over time.^{67,68} Manufacturers who submitted no compliance information in the compliance year for which NHTSA pulled analysis fleet data (perhaps because they had not yet commercialized products) are not included in the forward-looking compliance simulation. As a result, it is reasonable to expect, in future years beyond the rulemaking timeframe, that the composition of the fleet (in terms of nameplates offered, and manufacturer market shares) will look different than the CAFE Model’s projected compliance pathways. However, the technology content and overall performance predictions aggregated across industry remain prescient, despite the differences that will arise at the manufacturer or vehicle model levels.

⁶⁵ Mid-model year compliance data comprise manufacturers’ 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.

⁶⁶ The catalogue of reference specification sheets (broken down by manufacturer, by nameplate) used to populate information in the Market Data Input File is available in Docket No. NHTSA-2025-0491. These include BMW Data, Ferrari Data, Fiat Chrysler Automobiles (FCA) Data, Ford Data, Hyundai Data, INEOS Data, Kia Data, Mazda Data, Mercedes Data, Mullen Data, Nissan Data, Subaru Data, Toyota Data, Volvo Data, GM Data, Honda Data, Mitsubishi Data, VW Data, Jaguar Land Rover (JLR) Data, and Vinfast Data.

⁶⁷ The sales model in the CAFE Model does, at an industry level, adjust overall sales volume up or down, and sales share between light trucks and passenger cars, in response to technology costs, fuel economies, and fuel prices.

⁶⁸ DOT understands that nameplates (sometimes called a “badge”) 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 its position in that category with a new vehicle in the future that will be represented by that retired nameplate.

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 includes manufacturers’ 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 CAFE Model selects compliance pathways for future standards that affect vehicles already built in previous model years.⁶⁹

Though current data are highly desirable, real-time data to support fleet characterization in the Market Data Input File are extremely difficult to obtain. There is a lag time for finalized model year compliance data, meaning 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 the 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 uses mid-model year compliance submissions from MY 2024 to serve as the basis for the analysis fleets characterized in the Market Data Input File. Though the data used for this analysis are not the “final” data for MY 2024, 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. Because the CAFE Model must project any missing years between the starting year of the analysis (*i.e.*, MY 2024) and the initial year of the alternative scenario analysis (*i.e.*, MY 2027), relying on newer information (even if preliminary) improves the overall accuracy of compliance simulations.

To assemble the MY 2024 Market Data Input File, DOT staff must disaggregate compliance data to capture variation in curb weights, MSRPs, 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 subdivisions. 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 has limitations. 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 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.

⁶⁹ For example, in this analysis the CAFE Model must apply technology to the MY 2024 fleet in MYs 2025-2026 for the compliance simulation that begins in MY 2027 for the light-duty fleet. Though manufacturers have already built MY 2024 and later vehicles, the most current, complete dataset with regulatory fuel economy test results to build the analysis fleet available for this analysis remains MY 2024 data for the light-duty fleet.

Prior to the 2018 NPRM, DOT staff gave manufacturers the opportunity to share rolling resistance values and drag coefficients confidentially. In response to the 2016 Draft Technical Assessment Report (TAR), NHTSA received extensive comment from manufacturers that their prior efforts to improve aerodynamics and tire rolling resistance (ROLL) had not been characterized in the Draft TAR Market Data Input File. Many manufacturers volunteered confidential engineering data (aerodynamic drag coefficients, and ROLL values) to demonstrate this to 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. Though this took place in 2017, and was not repeated in subsequent years, in many cases the Market Data Input File for this analysis still references previously submitted CBI, even though manufacturers may have integrated newer rolling resistance and aerodynamic technologies over the past few years. When more recent or credible information is available, DOT staff supplement older CBI with recent studies and public information (such as data from published specification sheets). 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 verify. As a practical matter, DOT cannot conduct a teardown study of every vehicle in the fleet every time staff produce a new analysis fleet. Agency staff use engineering judgement, as well as information from suppliers, manufacturers, SwRI, and Argonne, 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. To do this, 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 look up the appropriate costs for each vehicle and fuel-saving technology. The CAFE Model also references battery costs for hybrid vehicle 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 10 technology classes supported by the CAFE Model. The assignment of a technology class to each vehicle model is discussed below. The CAFE Model defines 10 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.⁷⁰ 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 that normalizes the equation such that curb weight and footprint are more equally weighted.⁷¹ 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 base level of mass reduction technology (MR0) curb weight is calculated as part of the mass reduction level assignment process.⁷²

Equation 2-1: Size Fit Score

$$\text{Size Fit Score} = \frac{\text{Vehicle Sales}}{\text{Nameplate Sales}^{73}} \times \sqrt{\left(\frac{\text{MR0 CW}}{\text{lbs. per 1 sec}} - \frac{\text{Class Baseline CW}}{\text{lbs. per 1 sec}} \right)^2 + (\text{Vehicle FP} - \text{Class Average FP})^2}$$

⁷⁰ 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 in each technology class as assigned in previous analyses.

⁷¹ This quantity is calculated by multiplying the vehicle’s HP by 2.744 due to unit conversion for the fit, which is calculated on a 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.

⁷² For more information on how MR0 curb weight is calculated, see Chapter 3.4.2 Mass Reduction Analysis for Light-Duty Fleet Assignment.

⁷³ 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 or SmallSUVPerf). All rows for a nameplate now receive the same size technology 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.

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

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

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

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

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.

Equation 2-4: Pickup Fit Score

Pickup Fit Score

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

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, then 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 (mass reduction, 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,⁷⁴ 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.

A list of technologies supported by the CAFE Model is provided below, 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 MY 2024 fleet, effectiveness estimates, and considerations for their adoption, see the appropriate technology subchapters in Chapter 3 for more information.

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 research and development can pay off, and manufacturers may bring new fuel-saving technologies to market. The CAFE Model considers many technologies. Some are nearly universally adopted in the MY 2024 fleet, such as SGDI; some are used occasionally but show relatively high levels of effectiveness in terms of improving fuel efficiency, such as Variable Turbo Geometry (Electric) (VTGE). Similarly, costs of technologies in the future may be uncertain, but the analysis inputs assume that, over time, innovations will occur to lower the costs of many fuel-saving technologies. As manufacturers and suppliers bring technologies to market, intellectual property can significantly influence which manufacturers adopt technologies, and at what cost. Though 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 2-2.

Table 2-2: 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 Variable Valve Timing (VVT)	SOHC	Engines tab	Basic Engines
Double Overhead Camshaft Engine with VVT	DOHC	Engines tab	Basic Engines
Variable Valve Lift (VVL)	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

⁷⁴ For example, SHEVP2 paired with advanced engine technologies. See 3.1.1 for further discussion.

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 ¹	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
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 ²	CVT	Transmissions tab	Transmissions
Continuously Variable Transmission with Level 2 HEG ³	CVTL2	Transmissions tab	Transmissions
Conventional Powertrain (Non-Electric)	CONV	Vehicles tab	Basic Engine
12V Micro Hybrid Start-Stop System	SS12V	Vehicles tab	Hybrid Electric
48V Belt Mounted Integrated Starter/Generator	BISG	Vehicles tab	Hybrid Electric
Parallel Strong Hybrid/Electric Vehicle with DOHC Engine	P2D	Vehicles tab	Hybrid Electric
Parallel Strong Hybrid/Electric Vehicle with DOHC+SGDI Engine	P2SGDID	Vehicles tab	Hybrid Electric
Parallel Strong Hybrid/Electric Vehicle with SOHC Engine	P2S	Vehicles tab	Hybrid Electric
Parallel Strong Hybrid/Electric Vehicle with SOHC+SGDI Engine	P2SGDIS	Vehicles tab	Hybrid Electric
Parallel Strong Hybrid Electric Vehicle with TURBO0 Engine	P2TRB0	Vehicles tab	Hybrid Electric
Parallel Strong Hybrid Electric Vehicle with TURBOE Engine	P2TRBE	Vehicles tab	Hybrid Electric
Parallel Strong Hybrid Electric Vehicle with TURBO1 Engine	P2TRB1	Vehicles tab	Hybrid Electric
Parallel Strong Hybrid Electric Vehicle with TURBO2 Engine	P2TRB2	Vehicles tab	Hybrid Electric

Parallel Strong Hybrid Electric Vehicle with HCR Engine	P2HCR	Vehicles tab	Hybrid Electric
Parallel Strong Hybrid Electric Vehicle with HCRE Engine	P2HCRE	Vehicles tab	Hybrid Electric
Power-Split Strong Hybrid/Electric Vehicle with Full Time Atkinson Engine	SHEVPS	Vehicles tab	Hybrid Electric
Plug-in Hybrid Vehicle with TURBO1 Engine and 20-miles of electric range ⁴	PHEV20T	Vehicles tab	Hybrid Electric
Plug-in Hybrid Vehicle with TURBO1 Engine and 50-miles of electric range ⁴	PHEV50T	Vehicles tab	Hybrid Electric
Plug-in Hybrid Vehicle with HCR Engine and 20-miles of electric range ⁴	PHEV20H	Vehicles tab	Hybrid Electric
Plug-in Hybrid Vehicle with HCR Engine and 50-miles of electric range ⁴	PHEV50H	Vehicles tab	Hybrid Electric
Plug-in Hybrid Vehicle with Full Time Atkinson Engine and 20-miles of electric range ⁴	PHEV20PS	Vehicles tab	Hybrid Electric
Plug-in Hybrid Vehicle with Full Time Atkinson Engine and 50-miles of electric range ⁴	PHEV50PS	Vehicles tab	Hybrid Electric
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

¹ Technology that enables Miller Cycle ICE.

² The CVT technology is not applicable to the Pickup and PickupHT technology classes.

³ The CVTL2 technology is not applicable to the Pickup and PickupHT technology classes.

⁴ The PHEV20T, PHEV50T, PHEV20H, PHEV50H, PHEV20PS, and PHEV50PS are only evaluated in charge sustaining mode (gasoline operation) for the standard-setting analysis.

2.2.1.4. Air Conditioning Efficiency and Off-Cycle Fuel Consumption Improvement Values

The Market Data Input File includes information about AC efficiency and OC technologies; however, this information is not disaggregated at a vehicle model level. Instead, MY 2024 AC efficiency and OC values (in g CO₂/mi) are listed for each manufacturer, by regulatory class in the “Credits and Adjustments” tab of the Market Data Input File. The CAFE Model uses AC efficiency and OC values

which have been adjusted based on the regulatory scenario⁷⁵ during compliance simulation. Chapter 3.7 “Simulating AC Efficiency and Off-Cycle Technologies” shows model inputs specifying estimated adjustments (all in grams/mile) for improvements to AC efficiency and other OC energy consumption.⁷⁶ Additional information regarding a description of how manufacturers may generate FCIVs for AC and OC technologies under EPA’s regulations for measuring fuel economy can be found in preamble Section VI.

2.2.1.5. Engine Configurations

Different engine configurations may affect the cost of the engine and hybrid vehicle technologies.⁷⁷ 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. However, the standard-setting analysis only considers PHEVs in charge sustaining mode. If a hybrid electric powertrain replaces an internal combustion engine (ICE), the electric motor 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 mass reduction 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, then 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, vehicles that share transmissions have the same transmission code, and vehicles that adopt mass reduction technologies together share the same platform code.⁷⁸

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-saving technology

⁷⁵ As discussed in Chapter 2.1.5, the maximum allowable values (in g CO₂/mi), per EPA’s regulations, for AC efficiency and OC technologies are saved in the Scenarios Input File.

⁷⁶ For the light-duty fleet and to be consistent with EPA phase out, DOT assumes the AC values remain constant from 2024 through 2027 and OC values reduce to 10g/m in 2027, before those values are removed from the fleet in 2028. The AC and OC profiles and caps can be found in the Scenarios Input File.

⁷⁷ See Chapter 3.1.2 for a detailed discussion of engine classification based on cylinder count and configuration.

⁷⁸ 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. For example, two engines from the same manufacturer that have all the same architecture and technologies may share an engine code even if the HP output is slightly different or two transmissions from the same manufacture that use the same technology and number of gears may share a transmission code even if one or more gear ratios are slightly different.

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. Redesigns are major investments, and require coordination of product development, manufacturing, and marketing and sales. 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 6.7 years.⁷⁹

Even for manufacturers with similar times between redesigns that offer vehicles in similar segments, the expected timing of those vehicle redesigns would often occur at different times. When considering year-by-year analysis of standards, the timing of redesigns and the timing between redesigns often affect projected compliance pathways. The timing of redesigns, and the duration between redesigns, affect how quickly manufacturers may respond to standards.

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 mass reduction 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 (PC), crossover utility vehicle (CUV)/minivan, and light truck. Safety classes are entirely independent of CAFE regulatory classes; see Final TSD Chapter 7.3 for further discussion.

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 manufacturers’ compliance reports or specification sheets. The curb weight data in the compliance reports and specification sheets may be generally representative of the weight of a vehicle row. However, 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),⁸⁰ and the dealership employment associated with new vehicle sales. Labor information for MY 2024 by vehicle is included in the Market Data Input

⁷⁹ See Market Data Input File.

⁸⁰ Percentage U.S. content was informed by NHTSA. NHTSA, Part 583 American Automobile Labeling Act Reports, last revised: 2025, available at: <https://www.nhtsa.gov/part-583-american-automobile-labeling-act-reports> (accessed: May 25, 2026).

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 electric vehicle (EV) Federal tax credits (see Chapter 2.5.2) may affect percent U.S. content in the future. Some technologies may be more or less likely to be produced in the United States, and if that is the case, their adoption also 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 transmission could be replaced by another fuel-saving technology (like EMs and fixed gear boxes) that could require a meaningfully different amount of assembly labor hours.

Table 2-3 shows sales-weighted percent U.S. content by manufacturer, by regulatory class, for passenger automobiles and non-passenger automobiles, based on information collected from American Automotive Labeling Act (AALA) reports required by 49 CFR part 583.

Table 2-3: Sales-Weighted Percent U.S. Content by Manufacturer, by Light-Duty Regulatory Class

Manufacturer	PC (Pre-Reclassification)	LT (Pre-Reclassification)	PC (Post-Reclassification)	LT (Post-Reclassification)	Total MY 2024 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	6.2%	22.2%	13.51%	25.00%	14.3%	48.3%	-	-
Mercedes-Benz	0.2%	6.5%	0.17%	9.80%	3.9%	37.7%	12.5%	-
Stellantis	16.8%	56.9%	40.82%	62.07%	54.5%	73.3%	86.7%	94.2%
Ford	39.1%	25.1%	29.19%	25.06%	26.7%	67.8%	69.6%	94.4%
GM	26.9%	33.6%	25.34%	39.09%	31.4%	65.5%	56.8%	39.3%
Honda	54.1%	62.2%	57.61%	70.00%	57.9%	74.3%	87.4%	82.3%
Hyundai	2.9%	13.9%	6.28%	55.00%	8.7%	16.1%	11.5%	5.0%
Kia	15.1%	32.7%	24.88%		24.9%	46.7%	29.2%	46.7%
Jaguar Land Rover (JLR)	5.7%	3.6%	5.18%	3.01%	3.6%	-	-	9.1%
Mazda	4.0%	11.7%	10.95%		10.9%	17.2%	-	20.7%
Mitsubishi	0.4%	3.0%	2.30%		2.3%	-	0.2%	0.2%
Nissan	26.6%	37.9%	30.63%	33.50%	31.0%	61.6%	42.7%	14.6%
Subaru	18.9%	27.3%	26.19%		26.2%	65.1%	-	-
Toyota	46.1%	43.7%	48.24%	31.83%	44.6%	54.4%	80.9%	39.4%
Volvo	15.7%	0.0%	4.02%		4.0%	13.4%	-	-
VWA	3.1%	15.3%	33.06%	0.32%	11.2%	21.8%	1.0%	1.0%

As observed from Table 2-3, manufacturers employ U.S. labor with varying intensity. In many cases, non-passenger automobiles have a slightly larger percent U.S. content than passenger automobiles. This trend continues in many instances post reclassification, with the notable exception of the manufacturers that no longer have domestically assembled non-passenger automobiles in their fleets post reclassification.

2.2.2.3. Civil Penalty Payments

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. On July 4, 2025, OB3 (Pub. L. No. 119-21) revised 49 U.S.C. 32912 and reduced the civil penalty rate to \$0 for each 0.1 of a mile a gallon by which the applicable fuel economy standard exceeds the manufacturer’s average fuel economy. NHTSA has implemented this \$0 civil penalty rate value for all model years considered in the final rule analysis.

For this analysis, DOT has exercised the CAFE Model with inputs that assume all light-duty manufacturers will apply technology to the maximum practicable extent possible to avoid under-compliance with the standards. This means manufacturers will apply technology, when available, to reach compliance with the standards. These technologies are applied in order of cost effectiveness as determined by the CAFE Model. This methodology is discussed further in FRIA Chapter 4 and preamble Section II.

2.2.2.4. 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 dollar/gallon basis, this metric is computed by subtracting the estimated values of avoided fuel outlays, civil penalties (for this analysis, \$0), and Federal incentives (*i.e.*, available 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 standards in a given model year, the Model will apply any further fuel economy 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 36 months of vehicle operation.

2.3. Technology Effectiveness Values

The next set of 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, NHTSA uses full-vehicle modeling and simulation to estimate the fuel economy improvements that manufacturers could achieve by applying technology to a fleet of vehicles, 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 operating 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,⁸¹ 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. NHTSA simulates the model’s behavior predefined over test cycles, including the 2-cycle laboratory compliance tests (or 2-cycle tests),⁸² to determine how the individual components interact. The 2-cycle tests are test cycles used to measure fuel economy for CAFE compliance and are therefore the relevant test cycles for determining technology effectiveness when establishing CAFE standards. In the vehicle testing 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 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.⁸³

Full-vehicle modeling and simulation requires detailed data to capture 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 inputs 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 given 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

⁸¹ Each full-vehicle model in this analysis is composed of sub-models, which is why the full-vehicle model also could be referred to as a full-system model, composed of subsystem models.

⁸² EPA’s compliance test cycles measure a vehicle’s fuel economy. It is like running a car on a treadmill following two programs the “urban cycle,” or FTP, and the “highway cycle,” or Highway Fuel Economy Test (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.

⁸³ 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.

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 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. NHTSA uses the absolute fuel economy values from 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.⁸⁴ For subsequent technology changes, NHTSA applies 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. NHTSA determines the effectiveness values using full-vehicle simulations performed in Autonomie, a physics-based full-vehicle modeling and simulation software developed and maintained by DOE's Argonne National Laboratory.

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, NHTSA considers 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.

NHTSA determines the incremental effectiveness of technologies as applied to the thousands of unique vehicle and technology combinations in the analysis fleet. Though, 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 104 vehicle technology class models that are representative of large portions of the light vehicle fleet. The emblematic vehicle technology classes ensure that NHTSA reasonably represents 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. NHTSA considers over 50 technologies as inputs to the Autonomie

⁸⁴ See 2.2.1 2.2.1 Characterizing Vehicles and Their Technology Content for further discussion of CAFE compliance data.

modeling and simulation tool.⁸⁵ These inputs consist of engine technologies, transmission technologies, powertrain hybridization, light-weighting, aerodynamic improvements, and ROLL improvements. Chapter 3 broadly discusses each of the technology groupings definitions, inputs, and assumptions considered in the analysis. NHTSA includes 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.

NHTSA develops Autonomie model inputs considering real-world and compliance test cycle constraints. Examples of these constraints 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).

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. NHTSA developed 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 used for this analysis, developed by IAV and SwRI using their GT-POWER(c) Modeling tool (GT-POWER), 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.^{86,87} This ensures that the engine maps appropriately include real-world constraints as the Autonomie built vehicles are simulated on the test cycles.

Though the same engine map models are used for all vehicle technology classes, the effectiveness varies based on the characteristics of each vehicle 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.⁸⁸ For some Autonomie model inputs (for example, throttle time response and shifting strategies for different transmission technologies), assumptions are based on the latest test data and current market information.⁸⁹ The Autonomie tool did not simulate vehicle attributes that were determined to have minimal impacts on fuel economy, like

⁸⁵ See the following items in the rulemaking Docket No. 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 - 220811.xlsx; ANL - Summary of Main Component Performance Assumptions - (2b-3) FY22 NHTSA - 220811.xlsx.

⁸⁶ Engine knock in SI engines occurs when combustion of some 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 explode outside of the envelope of the normal combustion front.

⁸⁷ See IAV material submitted to the rulemaking Docket No. 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.

⁸⁸ An example of a default assumption is the DEAC methodology in Autonomie. The controller in Autonomie has been developed using test data to consider NVH and cold-start operation when to enable cylinder deactivation.

⁸⁹ See further details in 2.2.2.2 and Technology Pathways, Effectiveness, and Cost 3's individual technology pathway subchapters.

whether a vehicle had a sunroof or leather seats, as those attributes would have trivial impact in the overall analysis.

Because this analysis models 10 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). Given this, 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 also would increase the scale of the simulation effort by orders of magnitude. Instead, Argonne simulates 10 different representative vehicle technology classes. Technology classes are a means 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 unique Autonomie simulations for each technology class provides a specific set of simulations and effectiveness data for each technology class. The technology classes include five standard class vehicles (compact car, mid-size car, small SUV, mid-size SUV, pickup) plus five “performance” versions of these same body styles. The high performance and low performance vehicles classifications allow for better diversity in estimating technology effectiveness across the fleet.

Argonne developed a vehicle characteristics database to capture vehicle attributes 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 A2Mac1,⁹⁰ Argonne’s Downloadable Dynamometer Database (D³),⁹¹ EPA compliance and fuel economy data,⁹² EPA guidance on the cold-start penalty on 2-cycle tests,⁹³ the 21st Century Truck

⁹⁰ A2Mac1, Automotive Benchmarking, Proprietary data, available at: <https://www.a2mac1.com>, (accessed: Apr. 29, 2026). 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 many others. These components are weighed and documented for key specifications that are then available to subscribers.

⁹¹ Argonne National Laboratory, Downloadable Dynamometer Database, last revised: 2023, available at: <https://www.anl.gov/taps/downloadable-dynamometer-database> (accessed: Apr. 30, 2026).

⁹² EPA, Data on Cars Used for Testing Fuel Economy, last revised: May 19, 2025, available at: <https://www.epa.gov/compliance-and-fuel-economy-data/data-cars-used-testing-fuel-economy> (accessed: Apr. 30, 2026).

⁹³ EPA, Data on Cars Used for Testing Fuel Economy, last revised: May 19, 2025, available at: <https://www.epa.gov/compliance-and-fuel-economy-data/data-cars-used-testing-fuel-economy> (accessed: Apr. 30, 2026).

Partnership,^{94,95,96} and industry partnerships.⁹⁷ The resulting vehicle technology class characteristics assumptions database consists of over 100 different attributes, such as 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 10 vehicle types a set of initial attributes based on representative values determined from the compiled vehicle databases. For example, the characteristics of a MY 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 2-4 below shows 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,⁹⁸ and values for each vehicle technology class are provided with the Autonomie Input and Assumptions Description Files.⁹⁹

⁹⁴ DOE, 21st Century Truck Partnership: Research Blueprint, DOE: Washington, D.C. (2019), available at: https://www.energy.gov/sites/default/files/2019/02/f59/21CTPResearchBlueprint2019_FINAL.pdf (accessed: Apr. 30, 2026).

⁹⁵ DOE, 21st Century Truck Partnership, last revised: 2025, available at: <https://www.energy.gov/eere/vehicles/21st-century-truck-partnership> (accessed: Apr. 30, 2026).

⁹⁶ National Academies of Sciences, Engineering, and Medicine, Review of the 21st Century Truck Partnership: Third Report, *National Academies Press*: Washington, D.C. (2015), available at: <https://nap.nationalacademies.org/catalog/21784/review-of-the-21st-century-truck-partnership-third-report> (accessed: Apr. 30, 2026).

⁹⁷ North American Council for Freight Efficiency, Research & Analysis Are Fundamental, last revised: 2025, available at: <https://www.nacfe.org/research/overview> (accessed: Apr. 30, 2026).

⁹⁸ Chapter “Vehicle and Component Assumptions” of the CAFE Analysis Autonomie Documentation.

⁹⁹ 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 - 220811.xlsx; ANL - Summary of Main Component Performance Assumptions - (2b-3) FY22 NHTSA - 220811.xlsx.

Table 2-4: Reference Autonomie Technology Class Attributes, LD¹⁰⁰

Vehicle Class	Performance Category	0-60 mph Time (s)	Payload (kg)	Towing (kg)	Drag Coefficient	Tire Rolling Resistance	Frontal Area (m ²)	Estimated Curb Weight (kg)	Base Elec Acc Load (W)	Cold Start Penalty (bag1/bag2%) NA:TC ¹
Compact Car	Low	9	N/A	N/A	0.31	0.009	2.3	1337	250	14.3/1.084:15.8/1.096
Mid-size 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
Mid-size 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
Mid-size 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
Mid-size 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

NA = Naturally Aspirated. TC = Turbocharged Aspiration.

¹⁰⁰ These are the reference points for the baseline vehicles.

One notable vehicle attribute is engine mass. NHTSA does 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 curve 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 analysis fleet with an 8-cylinder engine adopts a more fuel-efficient downsized turbocharged 6-cylinder engine with the same performance level, the total vehicle weight reflects the updated engine weight with two fewer cylinders based on the peak power versus engine weight. The Autonomie simulation data accounts for the impact of engine mass reduction on effectiveness directly in the Autonomie simulation data through the application of the relationship curve described above. Engine mass reduction through downsizing is, therefore, appropriately not included as part of vehicle mass reduction technology that is discussed in Chapter 3.4, because doing so would result in double-counting the impacts. NHTSA uses four separate curves for light-duty: Two for naturally aspirated engines (one for gas and one for diesel) and two for turbocharged engines (one for gas and one for diesel); this improves the precision of the engine weight estimates.

In addition, NHTSA holds some attributes constant within each technology class to maintain vehicle functionality, performance, and utility, including NVH, safety, compliance with regulatory requirements, and other utilities important for customer satisfaction. This allows the analysis to capture discrete improvements in technology effectiveness while recognizing and accounting for real-world constraints that manufacturers face when making changes to certain vehicle attributes. 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, thus maintaining utility (*e.g.*, ground clearance, head-room space, and cargo space). Another example of an attribute NHTSA holds constant is the cold-start penalty used to account for fuel economy degradation for heater performance and emissions system catalyst light-off.¹⁰¹ This is done to ensure that the analysis does not change a vehicle attribute that could impact the vehicle’s compliance with criteria emissions standards.

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.¹⁰² 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 aerodynamic drag technology (AERO0), a base level of rolling resistance improvement (ROLL0), MR0, and corresponding attributes from the Argonne vehicle assumptions

¹⁰¹ The catalyst light-off is the temperature necessary to initiate the catalytic reaction and this energy is generated from the engine’s heat.

¹⁰² Further discussion of this process is in Chapter “Vehicle and Component Assumptions” of the CAFE Analysis Autonomie Documentation.

database like individual component weights.¹⁰³ 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.

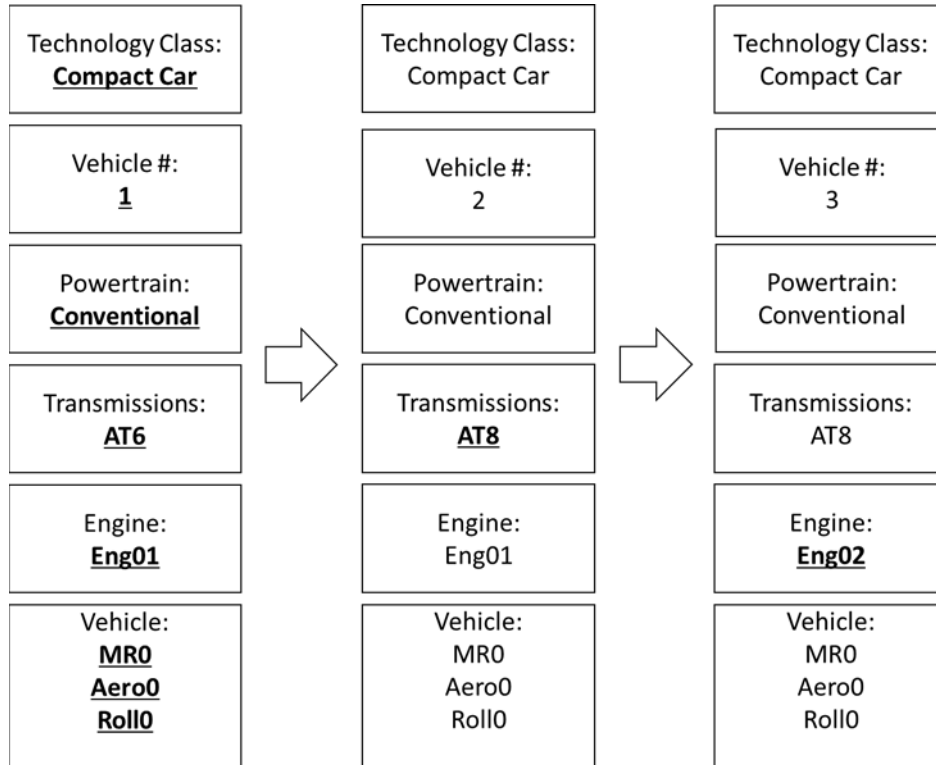
The next step in the process is to run a powertrain sizing algorithm that ensures the built vehicle meets or exceeds defined performance metrics, including low-speed acceleration (time required to accelerate from 0-60 mph), high-speed passing acceleration (time required to accelerate from 50-80 mph), gradeability (the ability of the vehicle to maintain constant 65 mph speed on a 6-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, NHTSA assigns an initial specific engine design and engine power, transmission, aerodynamic drag technology (AERO), tire rolling resistance, and mass reduction technologies as well as other attributes like 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 10 vehicle models (one for each technology class) are created, plus the 10 new vehicle models with the updated 8-speed automatic transmission, for a total of 20 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 2-3 shows a flow chart of the process for building vehicle models in Autonomie for simulation.

¹⁰³ Further discussion of this setup is in subchapter “Vehicle and Component Assumptions—Vehicle Component Weight Selection” of the CAFE Analysis Autonomie Documentation.

Figure 2-3: 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 hybrid vehicles (*e.g.*, HEVs or 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 mass reduction technologies.
- Vehicle performance is decreased or increased in response to the addition of a new technology like AERO or ROLL for the same hybrid vehicle.
- Hybridized vehicle battery size is decreased or increased in response to the addition, as applicable, of MR, AERO, and ROLL technologies.

Every time a vehicle adopts a new technology, the vehicle weight is updated to reflect the new component weight. For some technologies, 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, such as 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 because 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 remains technology-agnostic by using engine peak power instead of engine weight since it removes biases to any specific engine technology in the analysis. Though 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 2-4 shows an example of the engine mass regression for the naturally aspirated and forced air induction engines, and Figure 2-5 shows an example of 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.

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

Engine Mass vs. Engine Power Across Engine Type [Gasoline]

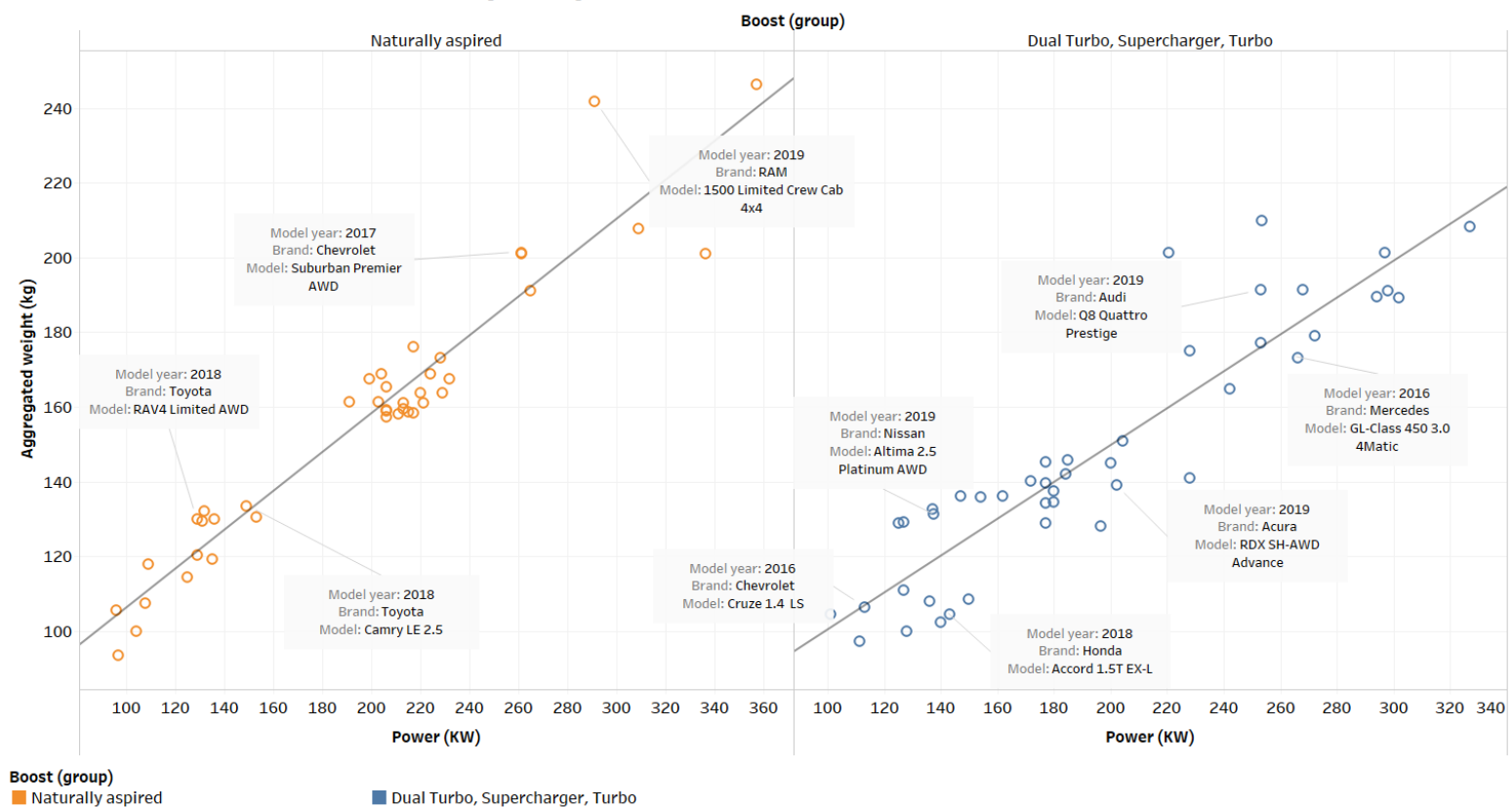
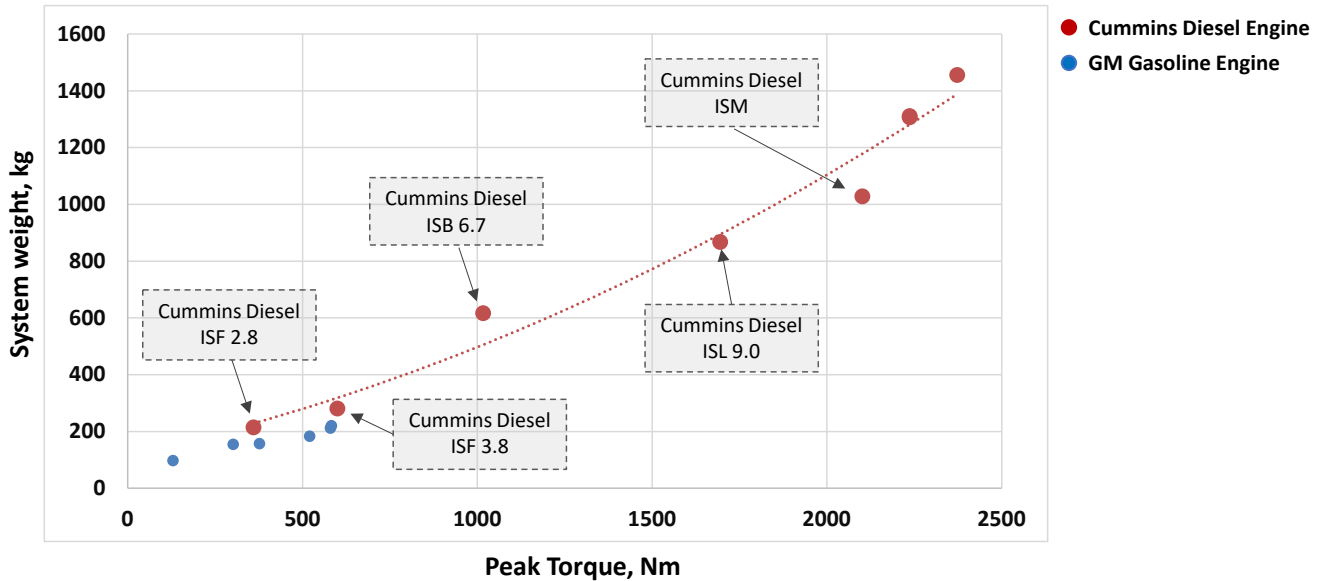


Figure 2-5: Diesel Engine Mass Determination as a Function of Power and Type of Air Induction and Engine Type

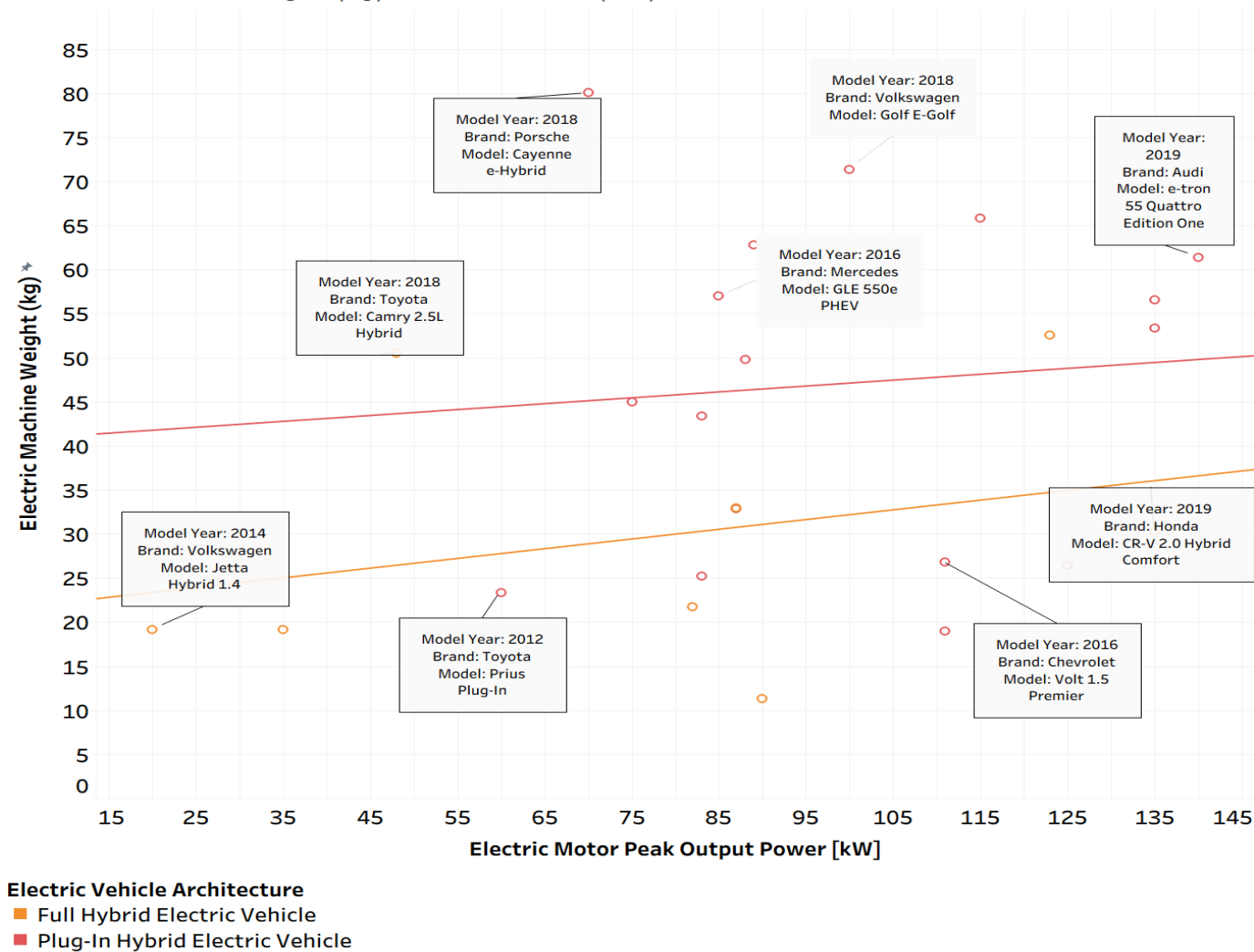


Like conventional vehicle models, Autonomie also builds hybrid vehicle models from the ground up. To capture improvements for hybrid vehicles for this analysis, Argonne applies the same mass regression analysis process that considers electric motor weight versus electric motor power for vehicle models that adopt electric motors. Argonne analyzed benchmarking data for hybrid and EVs from the A2Mac1 database to develop a regression curve of electric motor peak power versus electric motor weight.¹⁰⁴ Figure 2-6 below shows the electric motor mass regression as a function of peak power.

¹⁰⁴ 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

Electric Machine Weight (kg) vs. Peak Power (kW)



2.3.4. Sizing Powertrains

NHTSA maintains performance neutrality in full-vehicle simulations by resizing engines, electric machines, and 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 reflects how manufacturers consider engine resizing and product complexity and is consistent with DOT engineering experience with and observations of 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.¹⁰⁵ 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 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 2-3 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 hybridization 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.¹⁰⁶ 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 power-split strong hybrid electric vehicle (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, in the case of PHEVs with approximately 20-miles All-Electric Range (AER), the power of the motor/generators and battery must be sized to propel the vehicle through the Urban Dynamometer Driving Schedule (UDDS) cycle in “charge-depleting (CD) mode.” In this mode, the M/G alone (without assistance from the ICE) propels the vehicle; during high power demands, however, the engine may turn on and provide propulsion assistance. In the case of approximately 50-mile AER PHEVs, electric motor(s) and battery must be sized to power the vehicle through the US06 cycle in “EV mode,” where the engine is always off. It should be noted that Autonomie follows EPA regulatory guidance and uses the Society of Automotive Engineers (SAE) J1711

¹⁰⁵ For example, Ford EcoBoost engines are shared across 10 different models in MY 2019. Ford, Gas Power, Accelerated, available at: <https://www.ford.com/powertrains/ecoboost> (accessed: Apr. 30, 2026).

¹⁰⁶ Chapter “Vehicle Sizing Process” of the CAFE Analysis Autonomie Documentation.

test procedure to model the incremental effectiveness of adding PHEV technology to a vehicle.¹⁰⁷ For more information on PHEV resizing metrics and effectiveness algorithms,¹⁰⁸ see Chapter 3.3.4.

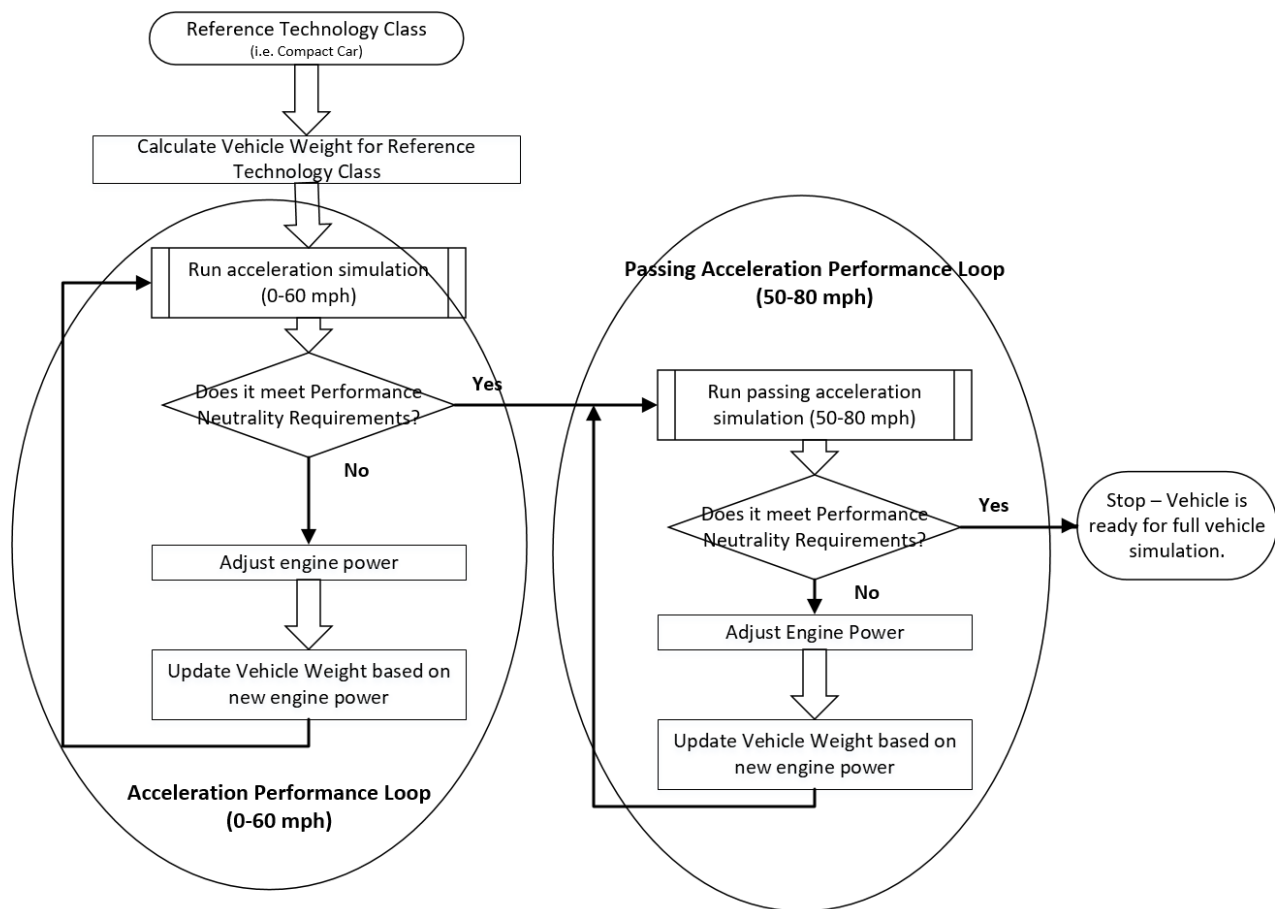
The powertrain sizing algorithm is an iterative process that attempts to optimize individual powertrain components at each step. For example, the sizing algorithm for CONV estimates required power to meet gradeability and acceleration performance and compares it to the reference engine power for the 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, such as 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 would be 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, 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, mass reduction 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 over-sizing components, engines, and electric machines and to minimize over and under-compliance in the analysis.

¹⁰⁷ Argonne has incorporated SAE J1711, Recommended Practice for Measuring Exhaust Emissions and Fuel Economy of Hybrid-Electric Vehicles, Including Plug-In Hybrid Vehicles, into the Autonomie modeling.

¹⁰⁸ 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.

Figure 2-7: Conventional Powertrain Closed Loop Sizing Algorithm



Depending on the type of powertrain considered, the sizing algorithms may resize to meet the different performance criteria in a different order. For example, the hybridized powertrain sizing algorithm considers different requirements. The powertrain sizing algorithms for hybrid vehicles are considerably more complex and are discussed in further detail in Chapter 3.3.4 and the CAFE Analysis Autonomie Documentation.¹⁰⁹

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 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 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.¹¹⁰

¹⁰⁹ CAFE Analysis Autonomie Documentation, Chapter titled “Vehicle Sizing Process—Vehicle Powertrain Sizing Algorithms.”

¹¹⁰ Chapter titled “Transmission Shifting” of the CAFE Analysis Autonomie Documentation.

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.¹¹¹

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.¹¹²

2.3.5. Performance Neutrality

The purpose of this analysis is to examine the impact of technology applications that can improve fuel economy. A fuel economy improvement can be realized by improving the powertrain that propels the vehicle (*e.g.*, by replacing a 6-cylinder engine with a smaller, turbocharged 4-cylinder engine) or by reducing the vehicle's loads or burdens (*e.g.*, by lowering aerodynamic drag, or reducing vehicle mass, rolling resistance, or both). Either way, these changes reduce energy consumption and create a range of choices for vehicle manufacturers. At the two ends of the range, the manufacturer can choose either:

A) To build a vehicle that does the same amount of work as before and uses less fuel as before.

For example, a redesigned pickup truck would receive a turbocharged V6 engine in place of the outgoing naturally aspirated V8. The redesigned pickup would offer no additional towing capacity, acceleration, larger wheels and tires, expanded infotainment packages, or customer convenience features, but it would achieve a higher fuel economy rating.

Or:

B) To build a vehicle that does more work and uses the same amount of fuel as before.

For example, a redesigned pickup truck would receive a turbocharged V6 engine in place of the outgoing naturally aspirated V8 but with engine efficiency improvements that allow the same amount of fuel to do more work. The redesigned pickup would offer increased towing capacity, faster acceleration, larger wheels and tires, an expanded (heavier) infotainment package, and more convenience features, while maintaining (not improving) the fuel economy rating of the previous year's model.

In other words, automakers weigh the trade-offs between vehicle performance/utility and fuel economy, and they choose a blend of these attributes to balance meeting fuel economy standards and meeting utility requirements.

¹¹¹ See Chapter titled "Transmission Shifting" of the CAFE Analysis Autonomie Documentation for more information on the shifting controller.

¹¹² See Chapter titled "Transmission Shifting" of the CAFE Analysis Autonomie Documentation for more information on the shifting initializer algorithm.

Historically, vehicle performance has improved over the years. The average HP is the highest that it has ever been; all vehicle types have improved HP by at least 69 percent compared to the MY 1975, and pickup trucks have improved by 77 percent.¹¹³ Since 1978, vehicles’ 0-60 acceleration time has improved by 43-50 percent depending on vehicle type.¹¹⁴ Fuel economy has also improved, but the HP and acceleration trends show that not 100 percent of technological improvements have been applied to fuel savings. Though future trends are uncertain, the past trends suggest vehicle performance is unlikely to decrease, as it seems reasonable to assume that customers will, at a minimum, demand vehicles that offer the same utility as today’s fleet.

For this rulemaking analysis, NHTSA analyzes technology pathways that manufacturers could use for compliance that attempt to maintain vehicle attributes, utility, and performance. Using this approach allows NHTSA to assess the costs and benefits of potential standards under a scenario where consumers continue to get similar vehicle attributes and features, other than changes in fuel economy. The purpose of constraining vehicle attributes is to simplify the analysis and reduce variance in other attributes that consumers may value across the analyzed regulatory alternatives. This allows for a streamlined accounting of costs and benefits by not requiring the values of other vehicle attributes that trade off with fuel economy. The CAFE Model maintains the initial performance and utility levels of the analysis fleet while considering real-world constraints faced by manufacturers.

To maintain performance neutrality when applying fuel economy technologies, it is first necessary to characterize the performance levels of each of the vehicle models in the baseline fleet. As discussed in Chapter 2.3.2, above, NHTSA assigned each individual vehicle model in the analysis fleet to one of ten vehicle “technology classes”—the class that is most similar to the vehicle model. The technology classes include five standard class vehicles (compact car, mid-size car, small SUV, mid-size SUV, pickup) plus five “performance” versions of these same body styles. Each vehicle class has a unique set of attributes and characteristics, including vehicle performance metrics, which describe the typical characteristics of the vehicles in that class.

The analysis uses four criteria to characterize vehicle performance attributes and utility:

- Gradeability (the ability of the vehicle to maintain constant 65 mph speed on a 6-percent upgrade); and
- Towing capacity.

Low-speed and high-speed acceleration target times are typical of current production vehicles and range from 6 to 10 seconds depending on the vehicle class; for example, the mid-size SUV performance class has a low- and high-speed acceleration target of 7 seconds. The gradeability criterion requires that the vehicle, given its attributes of weight, engine power, and transmission gearing, be capable of maintaining a minimum of 65 mph while going up a 6-percent grade. The towing criterion, which is applicable only to the pickup truck and performance pickup truck vehicle technology classes, is the same as the gradeability requirement but adds an additional payload/towing mass (3,000 lbs. for pickups, or 4,350 lbs. for performance pickups) to the vehicle, essentially making the vehicle heavier.

¹¹³ EPA, The 2024 EPA Automotive Trends Report: Greenhouse Gas Emissions, Fuel Economy, and Technology Since 1975, EPA-420-R-24-022, EPA: Washington, D.C. (2024), available at: <https://climateprogramportal.org/wp-content/uploads/2025/02/The-2024-EPA-Automotive-Trends-Report.pdf> (accessed: Apr. 30, 2026) (hereinafter, “The 2024 EPA Automotive Trends Report”). Figure 3.9 Average New Vehicle Horsepower by Vehicle Type.

¹¹⁴ The 2024 EPA Automotive Trends Report. Figure 3.13 Calculated 0-to-60 Time by Vehicle Type.

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.

When fuel-saving technologies are applied that significantly affect vehicle performance, such as replacing a pickup truck's V8 engine with a turbocharged V6 engine, Autonomie iteratively resizes the vehicle powertrain (engine, electric motors, and/or battery) such that the above performance criteria are maintained. For example, if the aforementioned engine replacement causes an improvement in acceleration, the engine may be iteratively resized until vehicle acceleration performance is shifted back to the initial target time for that vehicle technology class. For the low- and high-speed acceleration criteria, engine resizing iterations continue until the acceleration time is within plus or minus 0.2 seconds of the target time; this reasonably balances the precision of engine resizing with the number of simulation iterations needed to achieve performance within the 0.2 second window and the associated computer resources and time required to perform the iterative simulations.

The Autonomie simulation resizes until the least capable of the performance criteria is met to ensure the pathways do not degrade any of the vehicle performance metrics. It is possible that as one criterion target is reached after the application of a specific technology or technology package, other criteria may be better than their target values. For example, if the engine size is decreased until the low-speed acceleration target is met, it is possible that the resulting engine size would cause high-speed acceleration performance to be better than its target.

To address product complexity and economies of scale, NHTSA limits engine resizing to specific incremental technology changes that would typically be associated with a major vehicle or engine redesign. Manufacturers have repeatedly and consistently told NHTSA that the high costs for redesign and the increased manufacturing complexity that would result from resizing engines for small technology changes preclude them from doing so. It would be unreasonable and unaffordable to resize powertrains for every unique combination of technologies. Engine displacements are further described in Chapter 3.1.

To address this issue, the Autonomie simulations allow engine resizing when mass reduction is applied at several different levels and when one powertrain architecture is replaced with another architecture during a redesign cycle. At its refresh cycle, a vehicle may also inherit an already resized powertrain from another vehicle within the same engine-sharing platform. The analysis does not resize the engine in response to adding technologies that have smaller effects on vehicle performance. For instance, if MR1 is applied to a vehicle, causing the 0-60-mile per hour time to improve slightly, the Model would not resize the engine. This criterion better reflects what is feasible for manufacturers to do.

Because the regulatory analysis compares differences in impacts among the alternatives, NHTSA believes that having consistent performance across the alternatives is an important aspect of performance neutrality. If the vehicle fleet had performance gains that varied significantly depending on the alternative, performance differences would impact the comparability of the simulations.

2.3.6. 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.^{115,116,117} Argonne simulates each vehicle model across several test cycles to evaluate technology effectiveness. For vehicles with CONVs and micro hybrids, Autonomie simulates the vehicles per EPA 2-cycle test procedures and guidelines.¹¹⁸ For mild and strong HEVs, 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 J1711.¹¹⁹

2.3.7. Implementation in the CAFE Model

Though 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 uses only two elements of that information: battery costs and fuel consumption on the city and highway cycles. NHTSA combines the fuel economy information from the two cycles to produce a composite fuel economy value for each vehicle, and on 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.

Each Autonomie simulation record represents a unique combination of technologies, and NHTSA creates 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 (gpm) 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 hybridization, and no body-level improvements (mass reduction, aerodynamic improvements, or low rolling resistance tires). This is the reference point (for each technology class) for all the effectiveness estimates in the CAFE Model. The improvement factors that the Model utilizes 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 linked only 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, NHTSA established a unique group for each of these technologies.

As such, the following technology groups are defined within the modeling system: engine camshaft configuration (CONFIG), VVL engine technology, SGDI engine technology, cylinder deactivation, non-

¹¹⁵ EPA, How Vehicles Are Tested (2025), available at: https://www.fueleconomy.gov/feg/how_tested.shtml (accessed: Apr. 30, 2026).

¹¹⁶ Chapter titled “Test Procedures and Energy Consumption Calculations” of the CAFE Analysis Autonomie Documentation.

¹¹⁷ EPA, EPA Test Procedures for Electric Vehicles and Plug-In Hybrids: Draft Summary (2017), available at: <https://www.fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf> (accessed: Apr. 30, 2026).

¹¹⁸ 40 CFR 600.116-12 Special procedures related to EVs and HEVs.

¹¹⁹ PHEV testing is divided 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.

basic engine technologies (ADVENG), transmission technologies (TRANS), electrification (hybridization) technologies (ELEC), low rolling resistance tires, aerodynamic improvements (AERO), and mass reduction 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), mass reduction (level 1), electric power steering, and low-drag brakes, is specified as “SOHC; VVT; AT6; BISG; ROLL10; AERO20; MR1.”¹²⁰ 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 3 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 SHEVPS as a 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 vector¹²¹ while also adding SHEVPS, resulting in the following: SHEVPS; ROLL10; AERO20; MR1.

From here, it is relatively straightforward 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.¹²² 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.

2.4. Technology Costs

NHTSA estimates present and future costs of fuel-saving technologies by considering the type of vehicle, or type of engine when technology costs vary by application. These cost estimates are based on three main inputs. First, DMCs, or the component and labor costs of producing and assembling the physical parts and systems, are estimated assuming high-volume production. Second, NHTSA estimates indirect costs. DMCs generally do not include the indirect costs of tools, capital equipment, financing,

¹²⁰ 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.

¹²¹ For more discussion of how the CAFE Model handles technology supersession, see S4.5 of the CAFE Model Documentation.

¹²² 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 see S4.6 of the CAFE Model Documentation.

engineering, sales, administrative support, or return on investment. NHTSA accounts for these indirect costs via a scalar markup of DMCs, which is termed the RPE. Finally, the costs for technologies may change over time as industry streamlines design and manufacturing processes. To model this, NHTSA estimates potential cost improvements with cost learning. The retail cost of equipment in any future year is estimated to be equal to the product of the DMC, RPE, and cost learning. Considering the retail cost of equipment, instead of merely DMCs, 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. NHTSA 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 to estimate the DMCs of individual technologies. 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 where the tear-down study results differ significantly from credible independent sources, NHTSA scrutinizes the study assumptions and sometimes revises or updates the analysis accordingly.

Due to the variety of technologies and their applications, and the cost and time required to conduct detailed tear-down analyses, NHTSA did not sponsor teardown studies for every technology. In addition, the analysis includes certain fuel-saving technologies that are pre-production or sold in very small pilot volumes. For those technologies, NHTSA could not conduct a tear-down study to assess costs because the product is not yet in the marketplace for evaluation. In these cases, the agency relies upon third-party estimates and confidential information from suppliers and manufacturers; however, there are some concerns 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 or inaccurate information. In other cases, intellectual property considerations and strategic business partnerships may have contributed to a manufacturer's cost information and are difficult to account for in the CAFE Model, as not all manufacturers may have access to proprietary technologies at stated costs. In light of these concerns, NHTSA carefully evaluates new information, especially regarding emerging technologies.

Though 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 production expanded, and as nascent technologies mature. For emerging technologies, NHTSA uses 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, or hybridization) and the cost estimates the agency uses 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 that manufacturers are expected to use to improve the fuel economy of their fleets. 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 2-5 illustrates how these components can affect retail prices.

Table 2-5: 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, and operations	Cost of maintaining and operating manufacturing facilities and equipment
Corporate Overhead	
General and Administrative	Salaries of non-manufacturing labor, operations of corporate offices, <i>etc.</i>
Retirement	Cost of pensions for non-manufacturing labor
Health Care	Cost of health care for non-manufacturing 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, NHTSA must consider both direct and indirect costs. To estimate total consumer costs, NHTSA multiplies DMCs by an indirect cost factor to represent the average price for fuel-saving technologies at retail.

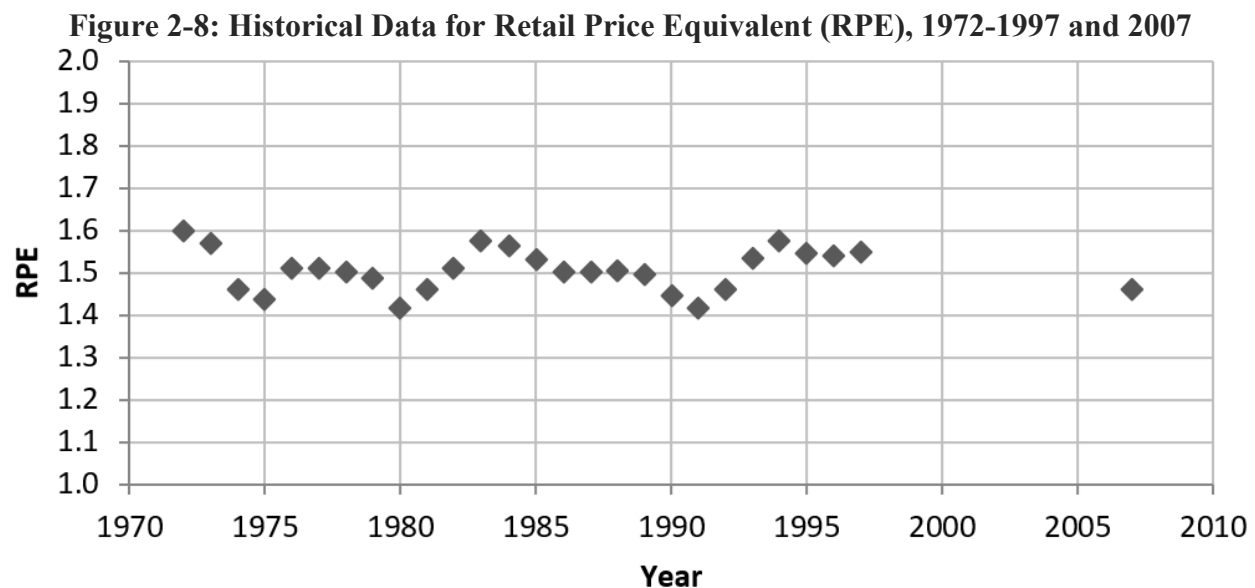
The most common method typically used to estimate indirect costs of producing a motor vehicle is the RPE. The RPE markup factor is based on an examination of historical financial data contained in 10-K reports filed by manufacturers with the Securities and Exchange Commission (SEC). It represents the 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 1.4.¹²³ From 1972-2007, the average annual

¹²³ Based on data from 1972 to 1997 and 2007. Data were not available for intervening years, but results for 2007 seem to indicate no significant change in the historical trend.

increase in real 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 DMCs.¹²⁴

An RPE of 1.5 does not imply that manufacturers indirect costs and profit margins for each vehicle equal 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 include a premium above DMCs at a higher or lower rate depending on indirect costs specific to that model and 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 over time and across the vehicle fleet, the retail price paid by consumers has risen by an average of \$1.50 for each dollar of DMCs incurred by manufacturers.



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 CAFE program used a 2002 NAS recommendation for RPEs of 1.5 for suppliers and 2.0 for in-house production be used on estimates of total costs. The former Alliance of Automobile Manufacturers (now referred to as The Alliance) also advocated these values as appropriate markup factors for estimating costs of technology changes. In their 2015 report, the NAS recommend 1.5 as an overall RPE markup. An RPE of 2.0 has also been adopted by a coalition of environmental and

¹²⁴ Rogozhin *et al.*, Automobile Industry Retail Price Equivalent and Indirect Cost Multipliers, Final, EPA-420-R-09-003, EPA: Ann Arbor, MI (2009), available at: <https://nepis.epa.gov/Exec/QueryPDF.cgi/P100AGJ1.PDF?Dockey=P100AGJ1.PDF> (accessed: Apr. 6, 2026).

research groups (Northeast States Center for a Clean Air Future [NESCCAF], International Council on Clean Transportation (ICCT), SwRI, and TIAX-LLC) in a report on reducing heavy truck emissions, and 2.0 is recommended by the U.S. DOE for estimating the cost of hybridization and automotive fuel cell costs (see Vyas *et al.* (2000) in Table 2-6 below). Table 2-6 below 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 2-6: Alternate Estimates of the RPE¹²⁵

Author and Year	Value, Comments
Jack Faucett Associates for EPA, 1985	1.26 initial value, later corrected to 1.7+ by Sierra research
Vyas <i>et al.</i> , 2000	1.5 for outsourced, 2.0 for OEM, hybrid vehicles
National Research Council (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, 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

As in previous CAFE and safety rulemaking analyses, NHTSA relies on the RPE to account for indirect manufacturing costs. The RPE accounts for indirect costs like engineering, sales, and administrative

¹²⁵ Duleep, K.G., Analysis of Technology Cost and Retail Price, Presentation to Committee on Assessment of Technologies for Improving Light-Duty Vehicle Fuel Economy, Detroit, MI (2008). As cited in National Research Council, Assessment of Fuel Economy Technologies for Light-Duty Vehicles, National Academies Press: Washington, D.C. (2011), available at: <https://nap.nationalacademies.org/catalog/12924/assessment-of-fuel-economy-technologies-for-light-duty-vehicles> (accessed: Apr 6, 2026); Jack Faucett Associates, Update of EPA's Motor Vehicle Emission Control Equipment Retail Price Equivalent (RPE) Calculation Formula, Report. No. 68-03-3244, EPA: Ann Arbor, MI (1985), available at: <https://nepis.epa.gov/Exc/ZyPURL.cgi?Dockey=940047LI.txt> (accessed: Apr. 6, 2026); McKinsey & Company, New Horizons: Multinational Company Investment in Developing Economies, Final version, McKinsey Global Institute: San Francisco, CA, Preface to the Auto Sector Cases, p. 1 (2003), 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 (accessed: Apr. 6, 2026); Transportation Research Board and National Research Council, Effectiveness and Impact of Corporate Average Fuel Economy (CAFE) Standards, National Academies Press: Washington, D.C. (2002), available at: <https://nap.nationalacademies.org/catalog/10172/effectiveness-and-impact-of-corporate-average-fuel-economy-cafe-standards> (accessed: Apr. 6, 2026); National Research Council, Assessment of Fuel Economy Technologies for Light Duty Vehicles, *The National Academies Press: Washington, D.C.* (2011), available at: <https://nap.nationalacademies.org/catalog/12924/assessment-of-fuel-economy-technologies-for-light-duty-vehicles> (accessed: Apr. 6, 2026); National Research Council, Cost, Effectiveness, and Deployment of Fuel Economy Technologies for Light Duty Vehicles, National Academies Press: Washington, D.C. (2015), available at: <https://doi.org/10.17226/21744> (accessed: Apr. 6, 2026) (hereinafter, "NRC (2015)"); Sierra Research, Inc, 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 (2007) (accessed: Sept. 10, 2025); Vyas, A. *et al.*, Comparison of Indirect Cost Multipliers for Vehicle Manufacturing, Center for Transportation Research: Argonne, IL (2000), available at: <https://publications.anl.gov/anlpubs/2000/05/36074.pdf> (accessed: Apr. 6, 2026).

support, as well as other overhead costs, business expenses, warranty costs, and return on capital considerations.

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 MYs 2012-2016. Both methods have been examined in subsequent rulemakings. NHTSA continues to employ the RPE approach as a cost multiplier for this analysis. A detailed discussion of indirect cost methods and the basis for NHTSA’s use of the RPE to reflect these costs is available in the FRIA for the 2020 Safer Affordable Fuel-Efficient (SAFE) rule.¹²⁶

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, reflects 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 declining cost levels. These learning curve estimates are applied to various technologies used to meet CAFE standards.

The concept of a learning curve was initially developed to describe cost reduction associated with improvements in manufacturing processes due to knowledge gained through experience in production. However, it has since been recognized that other factors make important contributions to cost reductions associated with cumulative production.¹²⁷ 60 years ago, Arrow noted that learning by doing was the acquisition of knowledge that increased productivity and included technological progress.¹²⁸ 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.¹²⁹ Clarke *et al.* also observed that empirically estimated learning curves can include both technological changes and scale economies.¹³⁰

NHTSA estimated cost learning 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 aircraft 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, which estimates the cost of the nth unit produced given the following

¹²⁶ U.S. Environmental Protection Agency and National Highway Traffic Safety Administration. The Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule for Model Years 2021-2026 Passenger Cars and Light Trucks; Final Rule. 85 FR 24174 (Apr. 30, 2020).

¹²⁷ Wene, C.O., Experience Curves for Energy Technology Policy, International Energy Agency, Paris (2000), available at: <https://doi.org/10.1787/9789264182165-en> (accessed: May 25, 2026).

¹²⁸ Arrow, K., The Economic Implications of Learning by Doing, *The Review of Economic Studies*, Vol. 29(3): pp. 155 – 73 (1962), available at: <https://doi.org/10.2307/2295952> (accessed: May 25, 2026).

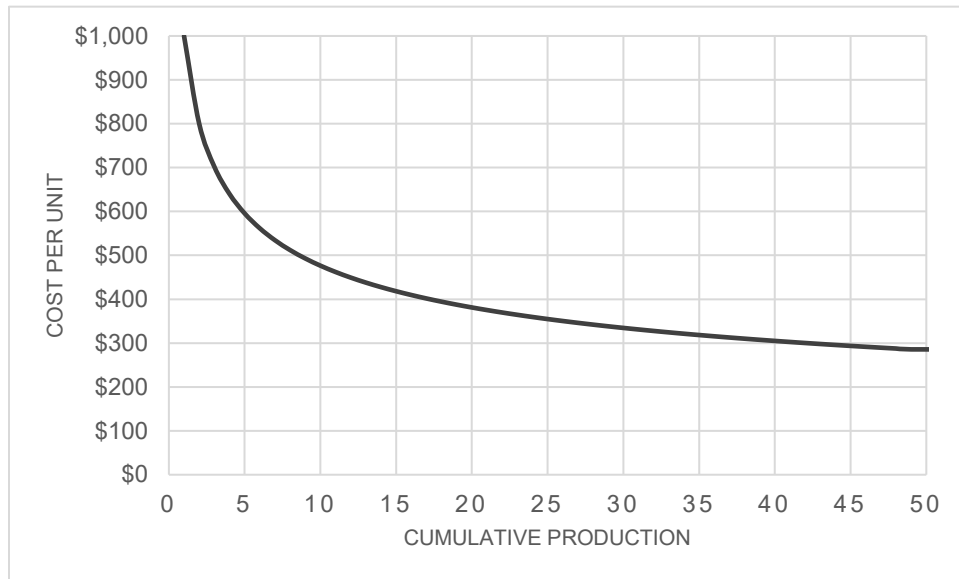
¹²⁹ Rubin, E. *et al.*, Experience Curves for Power Plant Emission Control Technologies, *International Journal of Energy Technology and Policy*, Vol. 2(1/2): pp. 52 – 69 (2004), available at: <https://escholarship.org/uc/item/503543gg> (accessed: May 25, 2026).

¹³⁰ Clarke, L. *et al.*, On the Sources of Technological Change: Assessing the Evidence, *Energy Economics*, Vol. 28(5–6): pp. 579 – 95 (2006), available at: <https://doi.org/10.1016/j.eneco.2006.05.004> (accessed: May 25, 2026).

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. Most technologies in the CAFE Model use Wright’s basic approach, where cost reduction is estimated by applying a fixed percentage to the projected cumulative production of a given fuel economy technology.

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



The analysis accounts for learning effects with model year-based cost learning forecasts for each technology that reduce DMCs 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 cost learning curves.

The following subchapter discusses NHTSA’s development of model year-based cost learning 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, NHTSA discusses how these learning effects are applied in the CAFE Model.

2.4.3.1. Time Versus Volume-Based Learning

For the 2012 final rule, NHTSA initially began developing learning curves as a function of vehicle model year. Though the concept of this methodology was derived from Wright’s cumulative production volume-based learning curve, its application for CAFE 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-percent to 3-percent cost reductions over a few years.

In their 2015 report to Congress, NAS recommended that NHTSA “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 standards.

In response, NHTSA has 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 were developed for the purpose of determining cost impact. For many technologies produced or sold in the United States, NHTSA obtained historical cumulative production data to establish a starting point for learning curves. Groups of similar technologies or technologies of similar complexity may share identical learning curves.

NHTSA estimated the slope of the learning curve, which determines the rate at which cost reductions occur, using research from an extensive literature review and automotive cost tear-down reports (see below). NHTSA derives the slope of the learning curve 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.

An EPA 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 2-7, 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. Though learning may have decelerated immediately after adding a second shift, NHTSA notes 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 2-7: Progress Ratios from EPA’s Literature Review

Author (Publication Date)	Industry	Progress Ratio (Cumulative Output Approach)
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Argote <i>et al.</i> (1997) as cited in Argote (2013) ¹³¹	Trucks	85%
Benkard (2000) ¹³²	Aircraft (commercial)	82%
Epple <i>et al.</i> (1991) ¹³³	Trucks	90%
Epple <i>et al.</i> (1996) ¹³⁴	Trucks	85%
Levitt <i>et al.</i> (2013) ¹³⁵	Automobiles	82%

In addition to the EPA literature review, NHTSA incorporated research from its own automotive cost-teardown studies. Evaluations of costs are routinely performed for previously issued FMVSS of new motor vehicles and equipment. NHTSA 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 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 FMVSS for MYs 1968-2012 passenger cars and light trucks and vans (LTV) (2017).¹³⁶

NHTSA chose five vehicle safety technologies for which there were sufficient data to estimate progress ratios. These specific technologies are large-volume technologies and are used by almost all vehicle manufacturers. Table 2-8 below includes these five technologies and yields an average progress rate of 92 percent:

Table 2-8: 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%

¹³¹ Argote, L. *et al.*, The Acquisition and Depreciation of Knowledge in a Manufacturing Organization - Turnover and Plant Productivity, Working Paper, Graduate School of Industrial Administration, Carnegie Mellon University (1997); Argote, L., Organizational Learning: Creating, Retaining and Transferring Knowledge, Springer: New York, NY (2013), available at: <https://doi.org/10.1007/978-1-4614-5251-5> (accessed: May 25, 2026).

¹³² Benkard, C. L. Learning and Forgetting: The Dynamics of Aircraft Production, The American Economic Review, Vol. 90(4): pp. 1034 – 54 (2000), available at: <https://www.aeaweb.org/articles?id=10.1257/aer.90.4.1034> (accessed: May 25, 2026)

¹³³ Epple, D. *et al.*, 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 (1991), available at: <https://www.jstor.org/stable/2634939> (accessed: June 3, 2026).

¹³⁴ Epple, D. *et al.*, An Empirical Investigation of the Microstructure of Knowledge Acquisition and Transfer through Learning by Doing, *Operations Research*, Vol. 44(1), pp. 77–86 (1996), available at: <https://www.jstor.org/stable/171906> (accessed: June 3, 2026).

¹³⁵ Levitt, S. *et al.*, Toward an Understanding of Learning by Doing: Evidence From an Automobile Assembly Plant, *Journal of Political Economy*, Vol. 121(4): pp. 643 – 81 (2013), available at: <https://www.nber.org/papers/w18017> (accessed: May 25, 2026).

¹³⁶ Simons, J. F., Cost and Weight Added by the Federal Motor Vehicle Safety Standards for MY 1968-2012 Passenger Cars and LTVs, Report No. DOT HS 812 354, NHTSA: Washington D.C., pp. 30 – 33 (2017), available at: https://downloads.regulations.gov/NHTSA-2021-0053-1643/attachment_44.pdf (accessed: May 25, 2026).

For a final progress ratio used in the CAFE Model, NHTSA averaged the five progress rates from EPA’s literature review and the five progress rates from NHTSA’s evaluation of automotive safety technologies results. This resulted in an average progress rate of approximately 89 percent. NHTSA placed equal weight 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

As discussed above, NHTSA obtained DMCs for each fuel economy-improving technology from various sources. To establish a consistent basis for DMCs in the rulemaking analysis, NHTSA adjusted each technology cost to 2024 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 DMCs 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, NHTSA can solve for an implied cost for the first unit produced. For some technologies, NHTSA used modestly different progress ratios to match detailed cost projections if available from another source (for instance, batteries for hybrid vehicles).

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 redoubling 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, NHTSA carefully examined direct costs with learning and adjusted the starting point for those technologies on the learning curve to 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, NHTSA applied learning effects to the incremental cost over the null technology state on the applicable technology tree. After this step, NHTSA calculated 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.

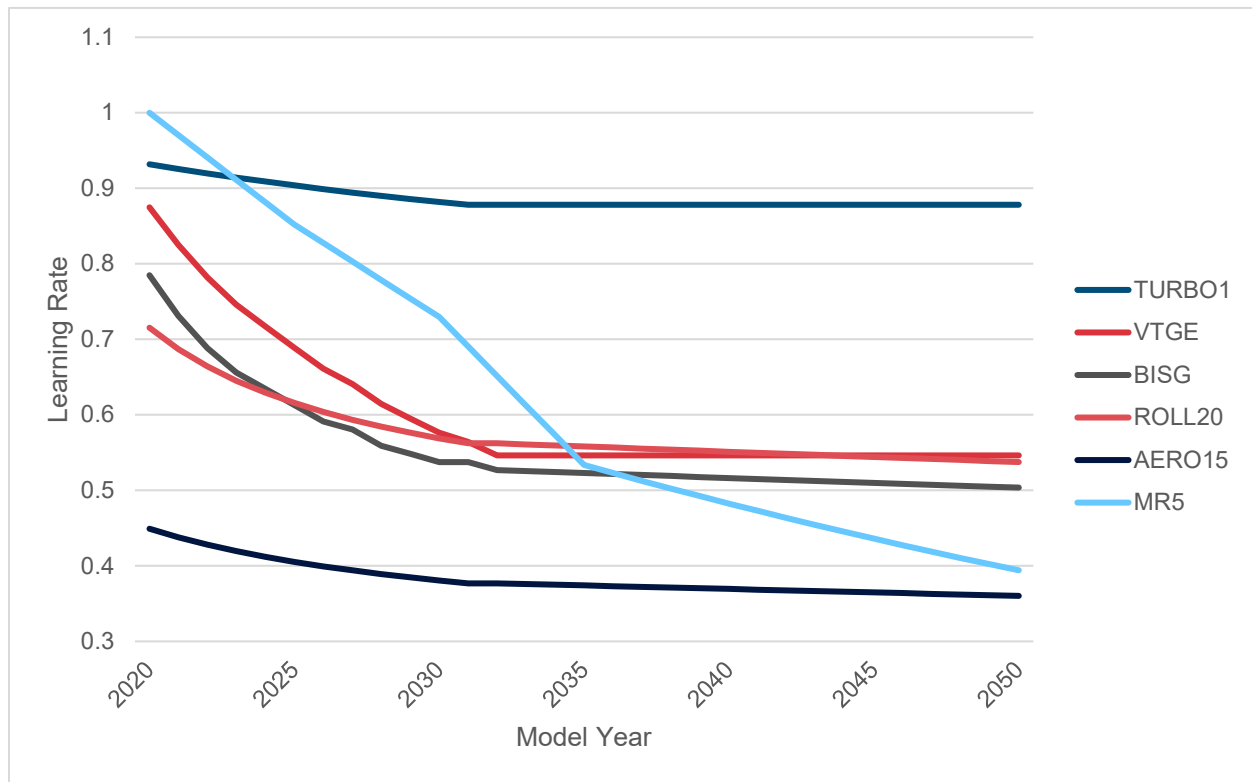
NHTSA grouped certain technologies, such as some advanced transmissions and non-battery hybrid vehicle components and assigned them to the same learning schedule. In addition, NHTSA assigned advanced engine technologies that are based on a singular preceding technology to the same learning curve as that preceding technology. Though the grouped technologies differ in operating characteristics and design, NHTSA chose to group them based on their complexity, technology integration, and economies of scale across manufacturers. For example, the low volume of some advanced technologies, such as hybrid 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.

NHTSA set model inputs for the explicit simulation of technology application from MYs 2020-2050. Accordingly, NHTSA updated the learning curves for each technology group to cover those same model years. For MYs 2020-2036, NHTSA expects incremental improvements in nearly all technologies, particularly in hybrid vehicle technologies, as a result of increased production volumes, labor efficiency, improved manufacturing methods, specialization, network building, and other factors; this contributes to continual cost learning, and NHTSA believes that many fuel economy-improving technologies considered in this rule will approach a flattened learning curve by MY 2036. Older and less complex engines and transmissions will reach a flattened learning curve sooner when compared to hybrid vehicle technologies, which have more opportunity for improvement. For SS12V batteries and non-battery components, NHTSA has estimated steeper learning curves beginning with MY 2020, which then gradually flattens after MY 2032; however, SS12V battery technology is expected to flatten at a slower rate. NHTSA estimates that learning curves for high-voltage battery packs—used in hybrid vehicles—will decrease between MYs 2020-2035 and then continue to decrease steadily for MYs 2036-2050. For more detailed discussions of the learning curves for conventional, hybrid vehicle non-battery, and hybrid vehicle battery technologies, see Chapter 2.4.4.1, Chapter 3.3.5.3.2, Chapter 3.3.5.3.1 respectively.

NHTSA assigns each technology in the CAFE Model 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 mid-size sedans and demonstrates that, while NHTSA estimates that such learning effects have already been almost entirely realized for engine turbocharging (a technology that has been in production for many years), NHTSA estimates that significant learning opportunities remain to reduce the cost of the greatest levels of mass reduction (*e.g.*, mass reduction level 5 or MR5) and even greater learning opportunities remain to reduce the cost of hybrid vehicle batteries. In fact, NHTSA concludes that some advanced technology costs that were estimated by using the standard learning curve progress ratio were not realistic, possibly due to unusual market prices, production relationships, or a combination of those two factors. For these technologies, NHTSA 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), VTGE, aerodynamic drag reduction by 15 percent (AERO15), MR5, 20-percent improvement in low rolling resistance tire technology (ROLL20), and belt integrated starter/generator (BISG).

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



2.4.4.1. Learning Curves for Conventional Technologies

When analyzing the learning curves for conventional vehicle technologies, NHTSA groups them into one of four categories: (1) basic engine technologies; (2) advanced engine technologies; (3) transmission technologies; and (4) rolling resistance technologies. NHTSA considers 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, NHTSA estimates the learning factor for these technologies to be 1.00 in MY 2020 and will continue to be flat through MY 2050. For other basic engine technologies (*i.e.*, VVL, SGDI, and DEAC), NHTSA estimates a relatively steep reduction in costs until MY 2036, when NHTSA expects costs to plateau and remain stable through MY 2050.

All advanced engine technologies follow the same general pattern—a steady reduction in costs until MY 2031 when they plateau and remain flat through MY 2050. Though all advanced engine technologies will have a steady reduction in costs until MY 2031, VTGE and advanced turbocharged downsized technology (TURBO2) have steeper declines than the other technologies; this is due to VTGE and TURBO2 being newer technologies with low production volumes and inefficient manufacturing processes. NHTSA expects their production volumes to increase and their manufacturing processes to improve at a faster rate, relative to the other advanced engine technologies, leading to economies of scale and a relatively greater reduction in costs by MY 2031.

In contrast, NHTSA considers the AT5 and AT6 transmissions to be mature technologies that will not experience any additional improvements in design or manufacturing. As a result, NHTSA estimates the learning factor for these technologies to be 1.00 and 0.99, respectively, in MY 2020 and estimates that they will remain flat through MY 2050. The remaining basic technologies (*i.e.*, AT8, DCT6, and DCT8) are nearly mature; therefore, they are estimated to experience a gradual reduction in costs from MYs 2020-2031, when they will plateau and then remain constant through MY 2050. Similarly, the learning

curves for the remaining transmissions are estimated to decrease from MYs 2020-2036 and then plateau and remain flat through MY 2050.

NHTSA estimates that the learning curves for all the road load technologies—with the exception of MR5—decrease from MYs 2020-2036 and then plateau and remain flat through MY 2050. The learning curve for MR5 follows a different curvature that gradually decreases from MYs 2020-2030, decreases sharper from MYs 2031-2035, and then continues to decrease from MYs 2036-2050 at a shallower rate. For further discussion on mass reduction technologies see Chapter 3.1.

In addition, the CAFE Model applies AC efficiency and OC technologies, and accounts for their associated costs independent of the technology pathways. As a result, NHTSA groups their learning curves together to maintain consistency. AC efficiency and OC technologies have a time-based learning curve, both of which NHTSA considers to be on the flat portion of the curve. Further discussion on AC efficiency and OC technologies is detailed in Chapter 3.7. Additional discussion of the AC efficiency and OC phaseout timeline is located in preamble Section II and Section VI.

Table 2-9 show the learning curve schedule for conventional technologies for MYs 2020-2035 and MYs 2036-2050, respectively.

Table 2-9: Learning Curve Schedule for CAFE Model Conventional Technologies, MYs 2020-2031

Technology	Model Year											
	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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

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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
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
OC	1.0000	0.9811	0.9686	0.9497	0.9371	0.9245	0.9107	0.8970	0.8835	0.8703	0.8572	0.8444

2.5. Simulating Existing Incentives

2.5.1. Overview of Tax Credits

NHTSA models three Federal tax credits that exist during some or all of the time period analyzed by the final rule when simulating the behavior of manufacturers and consumers. Due to EPCA’s constraints on considering the fuel economy of dedicated alternative fuel automobiles in determining maximum feasible standards, BEVs and FCEVs have been removed from the standard-setting analysis in their entirety. SHEVs are assumed to be ineligible for the tax credits. The tax credits are therefore only applied to PHEVs in the standard-setting analysis in modeling the pre-standard setting years for which they are applicable. Dual-fueled vehicles, such as PHEVs, may still be considered in the standard-setting analysis if they are cost effective when considering their operation solely on gasoline (alternatively known as charge sustaining mode).

The first credit modeled is the Advanced Manufacturing Production Credit (AMPC) (sec. 45X). This provision 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.¹³⁷ 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 to qualify for the \$10 per kWh module credit. OB3 created threshold percentages of material sources that have to be from a non-prohibited foreign entity to qualify for the AMPC tax credit and (also prohibits the manufacturer from claiming the credit if the manufacturer is a prohibited foreign entity).¹³⁸ The AMPC tax credits are available beginning with MY 2024 and phase out from 2030 to 2032.

The other two tax credits applied to qualifying vehicles at the time of purchase and are modeled jointly. The first, the Clean Vehicle Credit (sec. 30D),¹³⁹ provided 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.¹⁴⁰ This credit was available for PHEVs, BEVs, and FCEVs with MSRPs below \$55,000 for cars and \$80,000 for vans, SUVs, and pickups (though as discussed above, BEVs and FCEVs are not considered in the standard-setting analysis). Buyer eligibility was dependent on income levels for the credit offered in sec. 30D.

The second vehicle credit was the Credit for Qualified Commercial Clean Vehicles (sec. 45W), which provided up to \$7,500 toward the purchase of a vehicle with a gross vehicle weight rating (GVWR) of less than 14,000 pounds by a commercial entity for a purpose other than resale, and up to \$40,000 for

¹³⁷ 26 U.S.C. 45X. If manufacturers produce 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 and (ii) a credit equal to 10 percent of the manufacturing cost of critical minerals for battery production. NHTSA is not modeling these credits directly because of how NHTSA estimates battery costs and to avoid the potential to double-count the tax credits if they are included into other analyses that feed into NHTSA’s inputs. NHTSA 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 in the United States. The preponderance of component materials is mined outside the United States. Though NHTSA suspects the AMPC, coupled with other incentives, will induce some 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.

¹³⁸ Pub. L. No. 119-21, 139 Stat. 72.

¹³⁹ 26 U.S.C. 30D.

¹⁴⁰ There are vehicle price and consumer income limitations on the CVC, as well. See Congressional Research Service, Tax Provisions in the Inflation Reduction Act of 2022 (H.R. 5376) (2022), available at: <https://www.congress.gov/crs-product/R47202> (accessed: Apr. 7, 2026).

heavier vehicles. The credit value was the lesser of the incremental cost to purchase a comparable ICE vehicle, 15 percent of the cost basis for PHEVs, or 30 percent of the cost basis for FCEVs and BEVs. Among other requirements, a qualified commercial clean vehicle had to be acquired for use or lease by the taxpayer and not for resale. The credit was also available to a lessor of personal vehicles. Vehicles were eligible for either the sec. 30D or sec. 45W credit (collectively, CVC)—only one of the CVCs could be claimed for any given purchase.

OB3 ended sec. 30D and sec. 45W for vehicles acquired after September 30, 2025, and the two credits are therefore restricted to MYs 2024-2025 in the analysis.^{141,142}

2.5.2. 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. 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. However, 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 are sensitive to the relative elasticities of supply and demand. If demand is relatively elastic and supply inelastic, NHTSA expects 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, like the effect of an excise tax. This case is shown in Figure 2-11, 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 Q2.¹⁴³

¹⁴¹ Pub. L. No. 119-21, 139 Stat. 72.

¹⁴² While the IRS's definition of "acquired" would allow for some model years after 2025 to be eligible (*i.e.*, a MY26 vehicle being available in September 2025), for all practical purposes, we are restricting this to MY25 for modeling purposes.

¹⁴³ The economic theory demonstrated graphically in this subchapter can also be demonstrated mathematically. NHTSA presents the competitive market case here. The supply, q_s , and demand q_d , equations ($B < 0$, $b > 0$, $a < A$) are:

$$q_s = a + bp; q_d = A + Bp$$

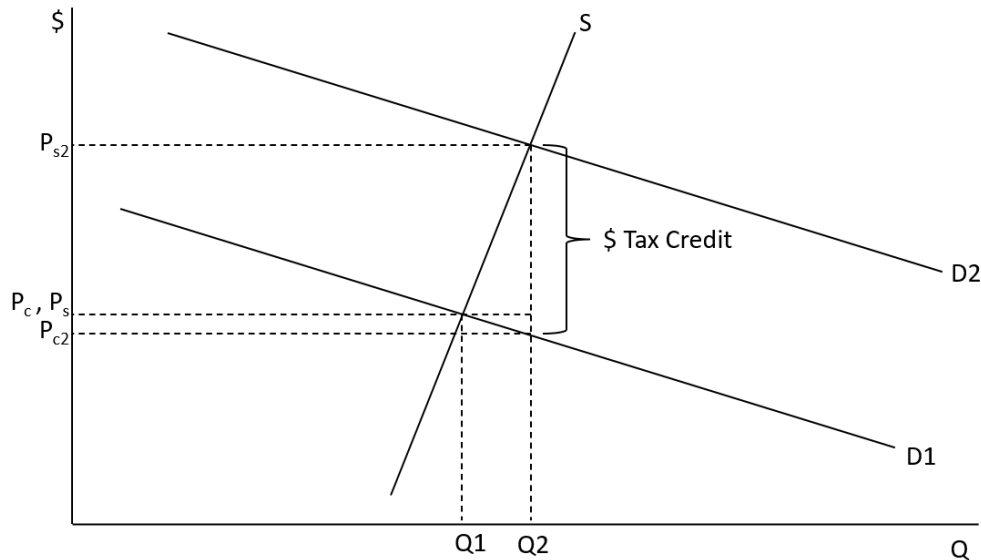
In equilibrium $q_s = q_d$, and the market price is:

$$p = \frac{a - A}{B - b}$$

If a subsidy of $x > 0$ per unit sold is given to the supplier, the equilibrium market price is found by solving:

$$q_s = a + b(p + x) = A + Bp = q_d$$

Figure 2-11: Elastic Demand, Inelastic Supply



If demand for eligible vehicles is highly inelastic and supply of eligible vehicles is highly elastic, the increase in eligible vehicles quantities would be modest and the tax credit would primarily be a transfer of taxpayers' money by the Government to eligible vehicle consumers. This is shown in Figure 2-12, where consumers see a large reduction in the effective price they pay (again from P_c to P_{c2}), while producers only see a small increase in the price they receive (from P_s to P_{s2}). Importantly, sales shift only modestly from $Q1$ to $Q2$.

$$p = \frac{a-A+bx}{B-b} = \frac{a-A}{B-b} + \frac{b}{B-b}x$$

The market price is reduced by $x[b/(B-b)]$. Though 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:

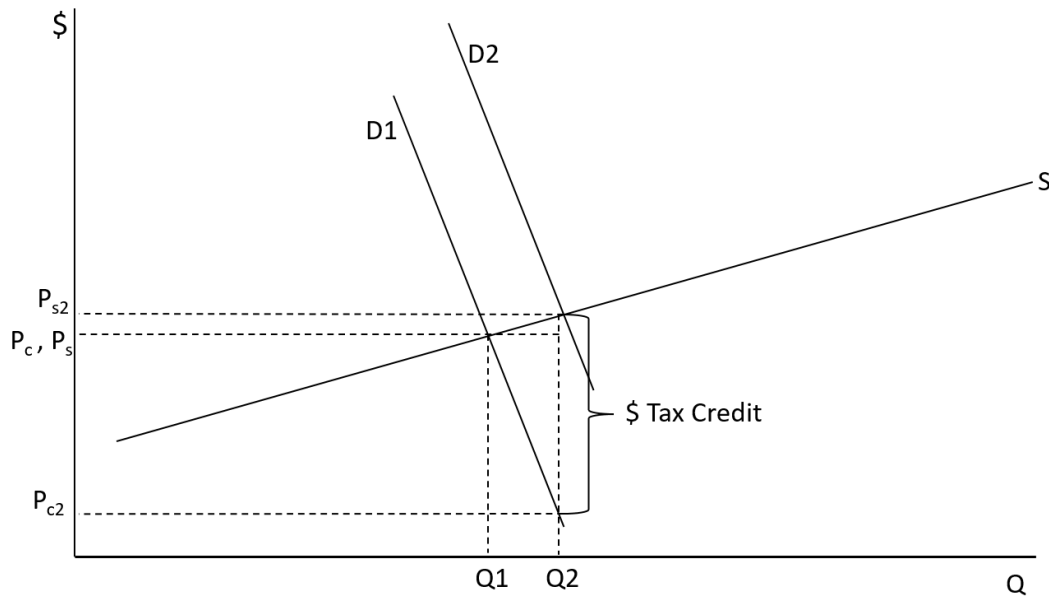
$$q_d = A + B(p-x) = a + bp = q_s$$

$$p = \frac{A-Bx-a}{b-B} = \frac{a-A}{B-b} + \frac{B}{B-b}x$$

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/q_s , p/q_d), and because in equilibrium supply = demand, the same ratios of price coefficients apply to ratios of elasticities. In terms of elasticities of demand (β_d) and supply (β_s), the subsidy x , is shared $x(\beta_s/(\beta_d - \beta_s))$ to the consumer and $x(\beta_d/(\beta_d - \beta_s))$ to the producer. Again, the sharing is 50/50 if $\beta_d = -\beta_s$.

Figure 2-12: Elastic Supply, Inelastic Demand



In both Figure 2-11 and Figure 2-12, 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 in between those extremes. Figure 2-13 shows the scenario where both supply and demand are inelastic and the sales response is small, while Figure 2-14 illustrates the case where both supply and demand are price-elastic, and the resulting sales response is large.

Figure 2-13: Inelastic Supply, Inelastic Demand

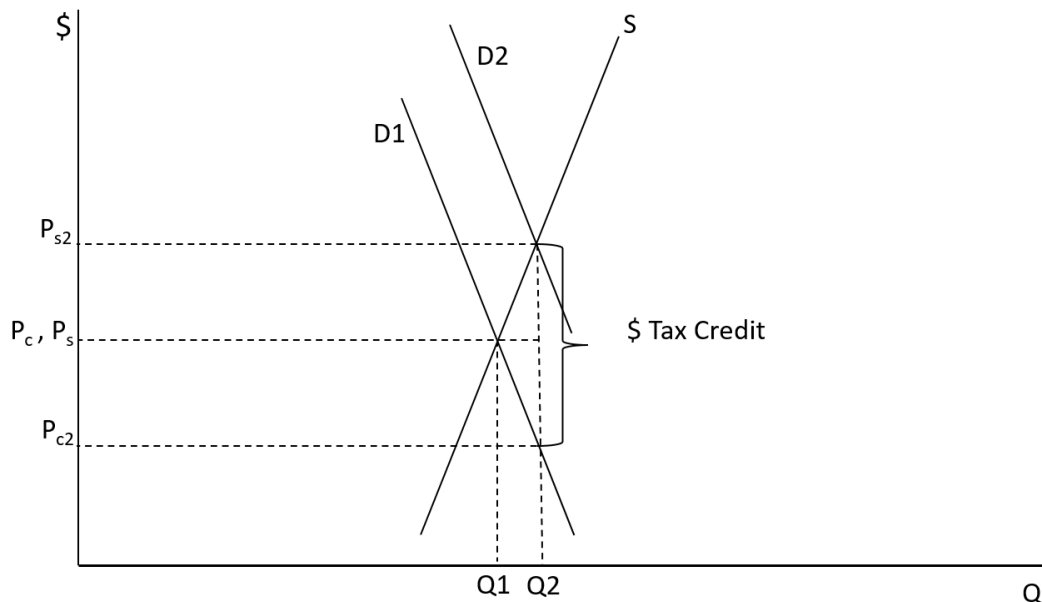
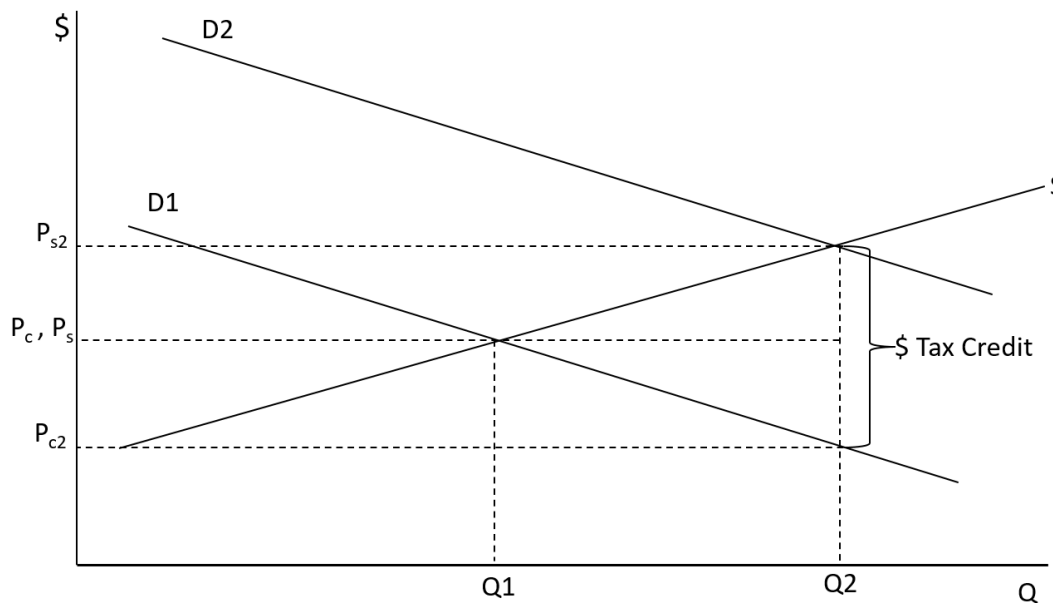


Figure 2-14: Elastic Supply, Elastic Demand



2.5.3. Implementation of Sections 45X, 30D, and 45W

Though 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. 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 (sec. 45X) and CVCs (secs. 30D and 45W). 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 that are modeled in the analysis.

The modeling approach to the AMPC includes several other restrictions, such as the terms of the credits and the limitations of the CAFE Model's structure to capture the tax credits precisely. The CAFE Model accounts for the MSRP restrictions of sec. 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, because these are ineligible for the tax credit. NHTSA cannot explicitly represent the income restrictions of sec. 30D in its analysis because the CAFE Model does not account for purchasers' income, and in any case, NHTSA does 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 sec. 30D income thresholds indirectly, insofar as high-income buyers are more likely to purchase luxury vehicles that exceed the sec. 30D's MSRP caps. NHTSA notes that sec. 45W does not feature these restrictions, but, unlike sec. 30D, it is available only to businesses and tax-exempt organizations (which includes firms that obtain vehicles to lease them as personal vehicles). Though the limitations under sec. 30D and sec. 45W differ with respect to MSRP caps, the total incentive values for the CVCs are based on the assumption that the majority of vehicles would be eligible under sec. 30D. Because the CAFE Model cannot distinguish between secs. 30D and 45W eligibility, the analysis applies the MSRP caps to all vehicles.

NHTSA's analysis also does not 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. Though the labor component of this analysis makes certain assumptions about the location of vehicle production, NHTSA does not have a reliable method or source to estimate where production is likely to occur during future model years. DOE-provided analysis, however, 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, NHTSA assumes that all eligible vehicles modeled during the timeframe 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. Rather than assuming a class-powertrain average capacity value¹⁴⁴ for determining the value of the AMPC credit, for this final rule, NHTSA allowed the credit value to be calculated separately for each vehicle¹⁴⁵ as the product of the dollars per-kWh credit value in the model year times the vehicle’s required battery capacity. This produces a more precise estimate of the credit’s expected value, and unlike its prior approach, is unaffected by vehicle reclassification. 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. To reflect this ramp-up, NHTSA reduces the modeled value of the AMPC in its first few years of availability. NHTSA chose a linear ramp of 40 percent per year starting in MY 2024 and continues a 20 percent ramp up per year until the credit is fully maximized for MY 2027. The AMPC is then phased out gradually beginning in MY 2030 and eliminated after MY 2032. Table 2-11 shows the assumed nominal and constant (2024 dollar) value of the AMPC per kWh by model year. The battery energy capacity values in Table 2-10 and credit values in Table 2-11 combine to produce total AMPC amounts by vehicle type in the CAFE Model’s Scenarios Input File.

Table 2-10: Tax Credit Values per kWh for the Advanced Manufacturing Production Credit¹⁴⁶

Model Year	Nominal \$/kWh	Real [\$2024/kWh]
2024	18	18
2025	27	26
2026	36	34
2027	45	42
2028	45	41
2029	45	40
2030	34	29
2031	23	19
2032	11	9
2033	0	0

¹⁴⁴ The estimated average battery capacity used in the NPRM was based directly from Argonne’s full-vehicle modeling, which used the average battery pack size pack for each vehicle class.

¹⁴⁵ The battery capacity used in the final rule is still based on Argonne’s full-vehicle modeling, but instead of the capacity values being averaged for each vehicle class, a capacity value for each vehicle is used instead for the final rule.

¹⁴⁶ Nominal values in future years are converted to constant 2024 dollars using the ratio of the GDP deflator in 2024, and rounded to the nearest dollar and the projected GDP deflator in the model year. Projections are taken from the AEO 2026 Alternate Transportation and Electricity Case Table 20, macroeconomic indicators, available at: <https://www.eia.gov/outlooks/aeo/data/browser/#/?id=18-AEO2026®ion=0-0&cases=electrnp&start=2025&end=2050&f=A&sourcekey=0> (accessed: Apr. 28, 2026).

NHTSA uses projected combined values of the CVCs provided by DOE. These values consider the latest information on penetration rates; retail prices; the share of U.S. sales that meet the critical minerals and battery component requirements of sec. 30D; the share of vehicles that exclude suppliers that are “Foreign Entities of Concern” as required by sec. 30D; and lease rates for vehicles that qualify for the sec. 45W CVC.¹⁴⁷ 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 2-11 shows the nominal and constant 2024-dollar values used in this analysis.

Table 2-11: Tax Credit Values for the Clean Vehicle Credit¹⁴⁸

Model Year	Nominal \$/vehicle	Real [\$2024]/vehicle
2024	4,200	4,200
2025	4,400	4,300

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 models/configurations in response to CAFE standards. The CAFE Model follows a year-by-year approach to simulating manufacturers’ potential decisions to apply technology, accounting for multi-year planning.

The CAFE Model accounts for multi-year planning using 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 multi-year planning, as well as a range of other factors represented by other model characteristics and inputs. These factors include inputs directing the Model to “skip” specific technologies for specific vehicle models/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 (HCR)); 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, NHTSA 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. Parts sharing includes the concepts

¹⁴⁷ DOE, Estimating Federal Tax Incentives for Heavy-Duty Electric Vehicle Infrastructure and for Acquiring Electric Vehicles Weighing Less Than 14,000 Pounds, DOE: Washington, D.C. (2024), available at: <https://downloads.regulations.gov/EERE-2021-VT-0033-0056/content.pdf> (accessed: Apr. 7, 2026).

¹⁴⁸ Nominal values in future years are converted to constant 2024 dollars using the ratio of the GDP deflator in 2024, and rounded to the nearest 100 dollars and the projected GDP deflator in the model year. Projections are taken from the 2026 AEO Alternate Transportation and Electricity Case Table 20, macroeconomic indicators, available at: <https://www.eia.gov/outlooks/aeo/data/browser/#/?id=18-AEO2026®ion=0-0&cases=electrnp&start=2025&end=2050&f=A&sourcekey=0>.

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 across 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.

Like vehicle platforms, manufacturers create engines that share parts. For instance, manufacturers may use different piston stroke lengths or piston bore diameters on common engine block castings 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 6- and 8-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 models/configurations in the analysis fleet that share engines belonging to the same platform are identified as such, and NHTSA also may apply a SKIP where NHTSA knows 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 consider engines as “common” 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. NHTSA considers engines together (for purposes of coding, discussed in Chapter 2.2 above, and for SKIP application) if the engines share a common manufacturer, cylinder count and configuration, displacement, valvetrain, turbocharger setup (or lack thereof), and fuel type, or if the engines only differ slightly in compression ratio (CR), HP, and displacement.

Parts sharing also includes the concept of sharing manufacturing lines (the systems, tooling, and assembly processes discussed above) because 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 time representing the “pace” of production that meets customer demand). 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 unrecovered—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,¹⁴⁹ is the MacPherson strut suspension. It is a popular low-cost suspension design and manufacturers use it across their fleet.

NHTSA has observed that manufacturers may be shifting their investment strategies in ways that 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 also 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 estimated accounting for refresh and redesign cycles, as well as 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 account for stranded capital. Adoption features specific to each technology, if applied on a manufacturer-by-manufacturer basis, are discussed in each technology subchapter. NHTSA will continue to monitor these trends to assess the role of stranded capital moving forward.

Finally, NHTSA ensures that its analysis is performance neutral because the goal is to capture the costs and benefits of adding fuel economy-improving technology *because* of the regulations, and not to capture costs and benefits inappropriately for changing other vehicle attributes that may have a monetary value associated with them.¹⁵⁰ This means that NHTSA will “SKIP” some technologies where NHTSA can reasonably assume that the technology would not be able to maintain a performance attribute for the vehicle, and where NHTSA’s 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, NHTSA also ensures that the analysis is performance neutral through other inputs and assumptions, like developing NHTSA’s engine

¹⁴⁹ Pilla, S. *et al.*, 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, SAE International: Warrendale, PA (2021), available at: <https://doi.org/10.4271/2021-01-0235> (accessed: May 25, 2026).

¹⁵⁰ See, e.g., 87 FR 25887 (Apr. 28, 2022), citing EPA, Consumer Willingness to Pay for Vehicle Attributes: What Is the Current State of Knowledge? EPA-420-R-18-016, EPA: Washington, D.C. (2018), available at: <https://pasteur.epa.gov/uploads/10.23719/1504203/documents/420r18016.pdf> (accessed: May 25, 2026). (“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 trade-offs 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 because 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.’”).

maps assuming use with a fuel grade most commonly available to consumers.^{151,152} 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; 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. For each technology, these inputs 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 only allow 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). For this analysis, all these inputs are set at levels that do not limit the simulation at all.

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. Using technology adoption features like phase-in caps and phase-in start years is one mechanism to ensure that the analysis better represents the potential costs and benefits of technology application in the rulemaking timeframe.

2.7. Vehicle Classification

Under EPCA, NHTSA is required to set maximum-feasible standards for two types of light-duty vehicles: passenger automobiles and non-passenger automobiles.¹⁵³ Vehicles in the light-duty fleet are classified into one of these two categories based on vehicle characteristics. EPCA separates vehicles into the two fleets based on whether the automobile has one (or more) of three features or characteristics that qualify it as a non-passenger automobile. The three categories of vehicles that qualify as non-passenger

¹⁵¹ See 85 FR 24386 (Apr. 30, 2020). (“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.”) (emphasis original).

¹⁵² *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.”).

¹⁵³ 49 U.S.C. 32902(b)(2).

automobiles are: (1) vehicles designed to transport more than 10 persons; (2) vehicles not primarily for transporting passengers; and (3) vehicles capable of off-highway operation. Under the statute, NHTSA is authorized and directed to “decide by regulation” whether a vehicle meets the criteria for non-passenger automobiles.

NHTSA conducted an analysis to determine how its current vehicle classification provisions at 49 CFR part 523 align with the intent of Congress when it enacted EPCA. As a result, NHTSA identified a misalignment between its current regulations and the statutory definitions and intent. In this rulemaking, NHTSA is changing its regulations at 49 CFR part 523 to align better with the original intent expressed in the statute, starting with MY 2030. Additional details about NHTSA’s reclassification effort can be found in Section VI of the final rule preamble.

2.7.1. Non-Passenger Analysis Fleet

To begin the analysis, NHTSA affirms that all vehicles currently classified as passenger automobiles are appropriately classified. Therefore, NHTSA’s analysis of the potential changes and their impacts on fleet compositions, is limited to those vehicles currently classified as non-passenger automobiles (also referred to as “light trucks” or “LT”). To conduct the analysis, NHTSA used data submitted by manufacturers to NHTSA in fuel economy compliance reports, as required in 49 CFR part 537. The reports use a standardized template consisting of multiple tabs containing data related to vehicle classification, footprint, and fuel economy. NHTSA used MY 2024 mid-model year compliance reports to build the analysis fleet. NHTSA combined all the non-passenger automobiles from each automaker, and the data supporting their inclusion in the non-passenger automobile fleet according to the characteristics described in 49 CFR 523.5, into a single dataset.

In each compliance report, there are often fewer carlines specified in the non-passenger vehicle classification tab as compared to the corresponding fuel economy tab. For example, a manufacturer may have produced 10,000 vehicles that all contain the same vehicle classification criteria, but 6,000 were produced with a 4-cylinder engine while the remaining 4,000 were produced with a 6-cylinder engine—resulting in a single row of data in the vehicle classification tab but two rows of data in fuel economy tab. To account for this, NHTSA resized the vehicle classification data to match the size of the fuel economy data, confirming that the production volumes were properly allocated and that the total volumes matched. This simplified the downstream process of building updated Market Data Input Files, which are used to re-evaluate the fuel economy curves to reflect the reclassified fleet composition. This curve setting analysis, detailed in Final TSD Chapter 1, requires the complete fuel economy data found only in the additional rows of the fuel economy compliance data.

In reporting qualification data for inclusion in the non-passenger fleet, it is common for manufacturers to populate only the minimum data to demonstrate qualification as a non-passenger automobile. For example, for a pickup truck that qualifies via 49 CFR 523.5(a)(3) or a 3-row vehicle that qualifies via 49 CFR 523.5(a)(5), the manufacturer may not have populated off-highway angles and clearances specified in 49 CFR 523.5(b)(2), even if the vehicle would have qualified via multiple non-passenger automobile pathways. To ensure a comprehensive dataset where “multi-path” vehicles were appropriately recognized, NHTSA performed a thorough quality assurance check using publicly available material to populate this missing data and verify existing data.¹⁵⁴ Having resized the non-passenger compliance reporting dataset to match the fuel economy compliance reporting dataset, NHTSA is able to be more

¹⁵⁴ The catalogue of reference specification sheets (broken down by manufacturer, by nameplate) used to populate and confirm missing information for vehicle reclassification is available in Docket No. NHTSA-2025-0491. These include BMW Data, Ferrari Data, FCA Data, Ford Data, Hyundai Data, INEOS Data, Kia Data, Mazda Data, Mercedes Data, Mullen Data, Nissan Data, Subaru Data, Toyota Data, Volvo Data, GM Data, Honda Data, Mitsubishi Data, VW Data, Jaguar Land Rover Data, and Vinfast Data.

specific in populating this missing data. For example, if a 3-row vehicle could be specified with a hybrid or conventional ICE powertrain and the hybrid has a reduced running clearance, the additional data line allowed inclusion of that distinction.

This MY 2024 non-passenger analysis fleet,¹⁵⁵ based on the current regulations and with alternative non-passenger pathway data added where necessary, forms the basis of all subsequent classification analyses. The classification analysis fleet contains 9.3M vehicles currently classified as non-passenger automobiles. This accounts for 67.9 percent of the total LD automobile fleet. As with the rest of this standard-setting rulemaking analysis, dedicated vehicles are not included in these values, pursuant to 49 U.S.C. 32902(h).¹⁵⁶

2.7.2. Finalized Changes to Non-Passenger Classification

To realign with EPCA, NHTSA analyzed a variety of non-passenger classification changes to evaluate their impacts on the overall light-duty fleet. NHTSA has built a tool to evaluate the impact of the various options on fleet sizes and list the vehicles that fell into each fleet.¹⁵⁷ The tool works by evaluating a series of logical arguments applied to each non-passenger pathway. By assigning TRUE (represented as whole numbers greater than 0) to a criterion that is met, and FALSE (represented as the value 0) to a criterion that is not met, an OR statement can be represented as a sum and an AND statement can be represented as a product.

As discussed in Final TSD Chapter 2.7.1, some vehicles may qualify as non-passenger automobiles via multiple pathways. Therefore, if any change removed a vehicle's non-passenger pathway via the existing regulations, the tool checked all other pathways that could requalify it for the non-passenger fleet before moving it to the passenger fleet. Historically, each requirement in 49 CFR 523.5(a) and (b) represented a unique logical criterion: 49 CFR 523.5(a) criterion were termed Functional Ability pathways, while 49 CFR 523.5(b) criterion were termed Off-Highway Ability pathways. Meeting any Functional Ability pathway OR the Off-Highway Ability pathway would result in a TRUE outcome for meeting non-passenger automobile criteria.

Because all analyses were performed using the MY 2024 non-passenger analysis fleet, the finalized changes “move” vehicles included in this fleet between the passenger and non-passenger automobile fleets to evaluate the impact of a regulatory change or combination of regulatory changes. When NHTSA states that a certain number of vehicles have “moved,” this represents a finalized change to the baseline fleet used for fuel economy footprint-based curve setting and the CAFE Model input with reclassification. The reclassification analysis does not “move” any MY 2024 vehicles for MY 2024 CAFE compliance, as the finalized regulatory changes would not take effect until MY 2030.

2.7.2.1. Third Row Seating Expanded Use Pathway

As described in Section VI of the preamble, NHTSA is removing 49 CFR 523.5(a)(5), which provides a pathway for vehicles to be classified as non-passenger automobiles if they have a standard third-row seat. This affects 2.8M vehicles out of the 9.3M total vehicles in the MY 2024 non-passenger analysis fleet; however, 1.6M of these vehicles meet alternative existing non-passenger criteria and would therefore

¹⁵⁵ See Non-Passenger_FRM_Analysis.xlsx, which can be found in the rulemaking docket (NHTSA Docket No. NHTSA-2025-0491) by filtering in Existing Reg Classification.

¹⁵⁶ See 90 FR 24518 (June 11, 2025).

¹⁵⁷ See Non-Passenger_FRM_Analysis.xlsx, which can be found in the rulemaking docket (NHTSA-2025-0491) by filtering in Reg Change Toggle and Fleet Outcome.

remain in the non-passenger fleet. A total of 1.2M vehicles in the MY 2024 non-passenger analysis fleet would thus be moved to the passenger automobile fleet as a result of this change alone.

2.7.2.2. Off-Highway Pathway

As described in Section VI of the preamble, NHTSA is removing the off-highway automobile characteristic for front and rear axle clearances in 49 CFR 523.5(b)(2)(v) and modifying 49 CFR 523.5(b)(2) to require that all four of the remaining criteria be met. Until this rule, four out of the five listed criteria were required to be met in order to qualify as a non-passenger automobile under the Off-Highway Ability pathway. NHTSA used the MY 2024 non-passenger analysis fleet to determine that, in terms of production volumes, of the vehicles that met the GVWR or 4-wheel drive off-highway criteria described in 49 CFR 523.5(b)(1) and exactly four out of the five existing off-highway criteria described in 49 CFR 523.5(b)(2):¹⁵⁸

- 98.9 percent do not meet the approach angle minimum threshold of 28 degrees.
- The remaining 1.1 percent of vehicles are from a single nameplate.¹⁵⁹
- 66.2 percent have an approach angle of less than the required departure angle of 20 degrees.¹⁶⁰

Complicating this analysis is the fact that some vehicle models can be optioned with adjustable or offroad suspensions.¹⁶¹ For the same reasons described in Final TSD Chapter 2.7.1, manufacturers often do not include a separate line item for vehicles equipped with suspensions that offered higher off-highway angles and clearances if the base suspension was sufficient to qualify under 49 CFR 523.5(b)(2), or if the vehicle qualified via some other pathway. In the case of adjustable suspensions, NHTSA has previously determined that:

it is appropriate . . . to measure the vehicles [sic] running clearance with the vehicles [sic] adjustable suspension placed in the position(s) intended for off-road operation under real-world conditions.¹⁶²

With approach angle as a required characteristic, several vehicles would meet this requirement if specified with their adjustable or off-road suspension option. NHTSA first researched and identified which nameplates, models, and trims could be specified with suspensions that offer increased ground clearance. By leveraging the additional rows in the non-passenger analysis fleet described in Final TSD Chapter 2.7.1, NHTSA adjusted the appropriate production volumes to reflect the presence of these vehicles in the non-passenger analysis fleet. For this final rule analysis, NHTSA also reviewed manufacturer comments that included vehicle level data and included them as part of the final rule analysis in the Market Data Input File.

¹⁵⁸ All percentages described were evaluated using Non-Passenger_FRM_Analysis.xlsx, which can be found in the rulemaking docket (NHTSA-2025-0491) by filtering for Existing Reg Classification.

¹⁵⁹ The Kia Seltos has a running clearance of 7.3 inches (~18.5 cm), below the 20-cm threshold. It has an approach angle of 28.0 degrees, meeting the minimum threshold.

¹⁶⁰ An approach angle less than the minimum required departure angle for off-highway capability would mean that the automobiles represented in this bullet are geometrically more capable off-highway when driven in reverse.

¹⁶¹ For example, certain Jeep Grand Cherokee trim packages can option or receive standard adjustable air suspensions that include ride height settings up to 2.5 inches greater than the standard suspensions, increasing running clearances and approaches, breakovers, and departure angles.

¹⁶² NHTSA, Interpretation ID: porschevrhs, last revised: 2004, available at: <https://www.nhtsa.gov/interpretations/porschevrhs> (accessed: June 9, 2026).

In some cases, the corresponding changes to off-highway angles associated with the optioned suspensions were not available. To account for these cases, NHTSA created an adjustable suspension calculator to determine these updated values based on known specifications.¹⁶³ The calculator uses simple trigonometry principles and therefore assumes no changes to vehicle geometry or tire contact point from the nominal suspension option aside from the raising and lowering of the vehicle. This would result in an underestimation in the final angles with the optioned suspension for this subset of vehicles that did not provide updated angles; however, where this calculation was used, the vehicle being evaluated either exceeded the minimum angles despite the underestimation or remained significantly below the minimum angle by more than the margin of error in the underestimation.

Equation 2-5: Approach and Departure Angle Adjustable Suspension Calculation

$$\theta_{AD} = \tan^{-1} \left[\frac{\tan(\theta_{ADN}) * h_M}{h_N} \right]$$

Where:

θ_{AD} = Approach or departure angle after adjusting suspension

θ_{ADN} = Nominal (known) approach or departure angle with standard suspension

h_M = Maximum ride height with adjustable or offroad suspension

h_N = Nominal ride height with standard suspension

Equation 2-6: Breakover Angle Adjustable Suspension Calculation

$$\theta_B = 2 * \tan^{-1} \left[\frac{\tan(\theta_{BN})}{2} + \frac{2 * \Delta h}{WB} \right]$$

Where:

θ_B = Breakover angle after adjusting suspension

θ_{BN} = Nominal (known) breakover angle with standard suspension

Δh = Increase in ride height over nominal ride height with standard suspension

WB = Wheelbase of the vehicle

Using the tool to toggle regulatory changes described in Final TSD Chapter 2.7.2, NHTSA determined that, if the changes to 49 CFR 523.5(b)(2) were applied alone, 3.7M vehicles out of the 9.3M total vehicles in the MY 2024 non-passenger analysis fleet would be moved to the passenger automobile fleet. When combined with the changes described in Final TSD Chapter 2.7.2.1, 6.4M vehicles would be moved to the passenger fleet. Because 1.6M vehicles currently qualify as non-passenger automobiles under both 49 CFR 523.5(a)(5) and 49 CFR 523.5(b), the overall effect of these finalized changes on the fleets is greater than the sum of applying each finalized change individually. The total of 6.4M vehicles that would be moved to the passenger vehicle fleet as a result of these finalized changes is the sum of the approximately 1.2M vehicles that would be moved to the passenger fleet as a result of the finalized

¹⁶³ See Non-Passenger_FRM_Analysis.xlsx, which can be found in the rulemaking docket (NHTSA-2025-0491) by filtering for Adjustable Suspension Calc.

change to 49 CFR 523.5(b)(2) alone, the approximately 3.7M vehicles that would be moved to the passenger fleet as a result of the finalized change to 49 CFR 523.5(b) alone, and the additional 1.6M vehicles that would be moved to the passenger fleet if both changes are made.¹⁶⁴

2.7.2.3. New Light-Duty Work Factor Pathway

NHTSA recognizes that, by removing 49 CFR 523.5(a)(5), some vehicles that have significant characteristics for the transportation of property would be classified as passenger automobiles. To address this, NHTSA is finalizing a new pathway into the non-passenger automobile fleet. To describe significant non-passenger characteristics, this finalized new pathway can be described independent of vehicle construction, platform, equipment, materials, or passenger-based metrics (such as rated cargo load¹⁶⁵ or seating arrangements) using a performance-based utility attribute. NHTSA is referring to vehicles that qualify for this new pathway as high-utility light-duty vehicles and is defining them using a Light-Duty Work Factor (LDWF) calculation. The process by which this new pathway was developed is described in detail below. Additional discussion of the LDWF can be found in Section VI of the final rule preamble.

2.7.2.3.1. Non-Passenger Metrics for Light-Duty Work Factor

NHTSA considered several non-passenger metrics for the LDWF, including a variety of weights, dimensions, and volumes. As discussed in Section VI of the final rule preamble, volume specifications are often incomplete in regulatory reporting and in publicly available manufacturer publications. Dimensions already set the basis for the fuel economy curves in both passenger and non-passenger fleets via the footprint-based curves. Other exterior dimensions fail to make distinctions between areas of the vehicle dedicated to the powertrain, passenger areas, and cargo areas. As with interior volumes, interior linear dimensions are also incomplete in regulatory reports or publicly available manufacturer publications. In addition, the unique shapes of various vehicles make the use of linear dimensions a poor proxy for utility.

Weight specifications, such as gross GVWR, gross combined weight rating (GCWR), curb weight, payload capacity, manufacturer rated towing capacity, and trailer weight rating (TWR)¹⁶⁶ are common automotive weight metrics that NHTSA evaluated in the final rule analysis for establishing a LDWF.

An unladen or laden vehicle's weight does not inherently imply its utility or ability to perform work, so curb weight or GVWR are poor standalone metrics for determining utility. However, when curb weight is subtracted from GVWR, as shown below, the resulting rated payload capacity is directly indicative of a vehicle's ability to perform work. The rated payload capacity is how much distributed weight can be placed inside or on the vehicle, such that all the weight is transferred solely through the vehicle's suspension, wheels, and tires. This includes the weight of passengers, cargo transported inside the vehicle, roof carriers, hitch carriers, and trailer tongue weight.

¹⁶⁴ The reported 6.4M is the result of summing the exact values versus the sum of the rounded values provided here, which sum to 6.5M. There are also five nameplates comprising a sales volume of around 65K vehicles that meet the current 49 CFR 523.5(a)(5) and (b)(2) and also meet the finalized modifications to 49 CFR 523.5(b)(2) described in this section; these vehicles are included in the 1.6M figure. The exact values used in NHTSA's analysis from the 2024 mid-model year FE reports are available in Non-Passenger_FRM_Analysis.xlsx, which can be found in the rulemaking docket (NHTSA-2025-0491) by filtering for Supporting & Related Material.

¹⁶⁵ As mentioned in 49 CFR 571.110 S.3, rated cargo load can be calculated as the vehicle capacity weight (payload capacity) minus 68 kg (150 lbs.) times the vehicle's designated seating capacity.

¹⁶⁶ SAE International Recommended Practice, Performance Requirements for Determining Tow-Vehicle Gross Combination Weight Rating and Trailer Weight Rating, SAE Standard J2807_202411, Reaffirmed Nov. 2024, last Revised Feb. 2020, Issued Apr. 2008, available at: https://doi.org/10.4271/J2807_202411 (accessed: May 25, 2026).

Equation 2-7: Payload Capacity, GVWR, and Curb Weight Relationship

$$[\text{Payload Capacity}] = [\text{GVWR}] - [\text{Curb Weight}]$$

GCWR, manufacturer rated towing capacity, and TWR then become the final weight-based metrics to consider. As with GVWR, GCWR as a standalone metric is not a direct indicator of a vehicle's ability to perform work. When GVWR is subtracted from GCWR, it does give a towing value, but that towing value can conflate the payload and towing capabilities of that vehicle. For example, if a 5,000-pound vehicle has a 1,500-pound payload, its GVWR would be 6,500 pounds. That same vehicle could have a manufacturer rated towing capacity of 7,000 pounds, but a GCWR of only 12,000 pounds. What this means is that if the vehicle has reached its payload capacity (inclusive of tongue weight), its towing capacity is reduced to only 5,500 pounds. By reducing this vehicle's payload, additional towing capacity is possible. Because NHTSA intends to consider the LDWF inputs separately (*i.e.*, in the case of payload and towing, how much payload a vehicle can carry when not towing, and how much a vehicle can tow when at a minimum operating payload), this method for determining towing capacity is not suitable.

Thus, manufacturer rated towing capacity and TWR become the final weight-based metrics to consider. Though both are measures of the maximum weight a vehicle can tow, TWR, as described in SAE J2807, is a standardized, testing-based procedure that ensures safety and capability across all vehicle aspects necessary for towing. It also ensures that all vehicles are held to the same standard when reporting towing capacity. In addition, it is already widely utilized in the U.S. light-duty market, particularly for high-towing light-duty vehicles, meaning that manufacturer rated towing capacity and SAE J2807 TWR are already synonymous for many light-duty vehicles.

When towing, only the trailer tongue weight, or the downward force that the trailer exerts on the tow hitch, is placed on the vehicle's suspension. As mentioned above, trailer tongue weight contributes to payload. Separate maximum towing capacities are often supplied for braked and unbraked trailers, where a braked trailer maximum capacity would be higher than unbraked. A braked trailer requires special vehicle wiring to supply electrical power to actuate the trailer brakes. On modern new vehicles, this is typically a 7-pin circular plug—the flat 4-pin plug only contains wiring for safety lighting, such as turn signals and brake lights.¹⁶⁷ Weight distributing hitches can also permit higher towing capability. NHTSA considers the maximum towing capacity with factory equipment, with additional equipment only as permitted and described in SAE J2807.

Therefore, payload calculated according to Equation 2-7 and TWR determined according to J2807 comprise the inputs for determining a vehicle's LDWF.

2.7.2.3.2. *How NHTSA Created the LDWF Analysis Fleet*

NHTSA ensured it had a comprehensive and accurate dataset for the 2024 fleet before starting the analysis by factoring in other finalized reclassification changes, including changes to off-highway operation. When analyzing the non-passenger automobile fleet, vehicles that qualify as non-passenger automobiles via 49 CFR 523(a)(1), (2), (3), or (4), and those that would qualify under the updated off-highway operation regulations in 49 CFR 523(b) described in Final TSD Chapter 2.7.2.2 were not considered in quantifying the LDWF. The reason for their omission in the LDWF analysis is that these vehicles qualify via other non-passenger automobile pathways and were therefore designed with other chief non-passenger characteristics—their inclusion could therefore skew the results of those vehicles that would only potentially qualify for the non-passenger automobile based on enhanced non-passenger utility.

¹⁶⁷ SAE International, Automotive Trailer Tow Connector, SAE Standard J2863_202302, Warrendale, PA: SAE International (2023), available at: https://doi.org/10.4271/J2863_202302 (accessed: May 25, 2026).

Note that the LDWF Analysis Fleet is a subset of the Non-Passenger Analysis Fleet described in Final TSD Chapter 2.7.1.

In performing the fleet analysis to set a LDWF threshold to qualify as a non-passenger vehicle, NHTSA recognized that many vehicles could be specified with or without a trailering package (also commonly referred to as a “tow package” or “towing package”). These packages can range from minor changes, such as the inclusion of trailer wiring and a tow hitch, to more significant changes, such as larger cooling packages, an enhanced suspension, a change to the final drive ratio, or reinforced driveline components. These changes do not significantly impact the powertrain or 2-cycle fuel economy of the base vehicle. In other words, trailering packages unlock utility that the powertrain and vehicle platform were already designed to provide. Therefore, in defining fleet composition for the passenger and non-passenger MY 2024 baseline fleets, NHTSA assumes that, in the future, manufacturers will not remove trailering capability as standard equipment on vehicles that would qualify as non-passenger automobiles via the LDWF non-passenger automobile pathway when equipped with the trailering hardware that they were designed to include. This assumption extends to the hardware and weight specifications considered in SAE J2807,¹⁶⁸ such as adding a tow hitch receiver to a vehicle that did not include one from factory, but whose platform and powertrain is otherwise capable of providing an SAE J2807 trailer weight rating. Modifications to the platform or powertrain beyond that which is specified in SAE J2807 are outside the scope of determining a vehicle’s LDWF.

In addition, NHTSA was unable to verify adherence to SAE J2807 across all vehicle’s manufacturer rated towing capacities represented in the LDWF Analysis Fleet. NHTSA assumes that the values reported by manufacturers across the LDWF Analysis Fleet vehicles are suitable proxies for a vehicle’s SAE J2807 TWR, and that by moving the classification effective date to MY 2030, manufacturers will have sufficient time to provide the SAE J2807 TWR as their manufacturer rated towing capacity for their high-utility light-duty vehicles.

The following steps summarize how NHTSA compiled the vehicle fleet used in the LDWF analysis:

- Compile all MY 2024 non-passenger vehicles using the existing classification regulations from manufacturer-reported compliance data.
- Perform quality checks on the data, including confirmation of reported values and populating missing data using publicly available material and relevant comment response data from manufacturers.
- Remove vehicles that qualify as non-passenger automobiles via any of the following pathways:
 - Transport more than 10 persons;
 - Provide temporary living quarters;
 - Transport property on an open bed;
 - Provide, as sold to the first retail purchaser, greater cargo-carrying than passenger-carrying volume; and
 - Have either four-wheel drive or a GVWR > 6000 lbs., and meets all four of the following criteria:
 - Approach angle of not less than 28 degrees;
 - Breakover angle of not less than 14 degrees;
 - Departure angle of not less than 20 degrees; and

¹⁶⁸ SAE International Recommended Practice, Performance Requirements for Determining Tow-Vehicle Gross Combination Weight Rating and Trailer Weight Rating, SAE Standard J2807_202411, Reaffirmed Nov. 2024, last Revised Feb. 2020, Issued Apr. 2008, Section 5.2., available at: https://doi.org/10.4271/J2807_202411 (accessed: May 25, 2026).

- Running clearance of not less than 20 centimeters.
- Apply the maximum towing capacity available on that nameplate, configuration, and trim.

The remaining vehicles were then subjected to a subsequent analysis using their rated payload and towing capacities, as defined in Equation 2-7 above.

2.7.2.3.3. *Weighting Payload vs. Towing for the LDWF*

The concept of a payload and towing work factor (WF) is not novel for NHTSA. In the heavy-duty pickup trucks and vans (HDPUV) program, the FE curves are based on a WF attribute instead of the footprint attribute used in the LD program. In HDPUV, the WF attribute is calculated as:

Equation 2-8: HDPUV Work Factor¹⁶⁹

$$HDPUV\ Work\ Factor = [0.75 * (Payload\ Capacity + Xwd)] + [0.25 * Towing\ Capacity]$$

Where:

Payload Capacity is GVWR minus curb weight.

Xwd is a 500-pound adjustment for the presence of four-wheel drive.

Towing Capacity is GCWR minus GVWR.

NHTSA recognizes that a WF calculated as the sum of weighted factors only contains value as a relative metric. In other words, the HDPUV WF as a standalone value on a single vehicle is not an inherently useful metric; however, when applied to the entire HDPUV fleet, the relative values across the fleet convey a useful relationship between the work an HDPUV can perform and its FE. Similarly, the LDWF applied to LD automobiles will define a useful comparative utility metric across the LDWF Analysis Fleet.

In the HDPUV program, by setting the weighting at 75 percent for payload and 25 percent for towing, NHTSA effectively stated that increasing a vehicle's WF by 1 would require increasing its payload capacity by 1.33 pounds or increasing its towing capacity by 4 pounds. Because the HDPUV WF is used as the x-axis attribute in the HDPUV fuel efficiency curves, this weighting makes sense; HDPUV vehicles perform their fuel economy test cycles at their Adjusted Loaded Vehicle Weight (ALVW),¹⁷⁰ so the payload capacity is significantly incorporated into the fuel efficiency test cycle procedures.

Though HDPUV WF is an attribute to establish fuel efficiency standards, the LDWF is a characteristic to determine non-passenger utility. As such, it is necessary for the vehicle to have been manufactured primarily for transporting property. This means that the design contains chief characteristics supporting payload and towing capacities; these design considerations differ between payload and towing.

Designing for a higher payload capacity includes considerations for axle, frame, suspension, wheel, and tire capacities. These higher capacity components add weight to the vehicle, and when combined with the additional payload capacity may require only modest enhancements to the powertrain and driveline to maintain performance and utility characteristics.

In contrast, designing for a higher towing capacity includes considerations for pulling, including frame reinforcements to resist trailer forces acting opposite the direction of motion, increases to powertrain

¹⁶⁹ 49 CFR 535.5(a)(2)(ii).

¹⁷⁰ Definition at 40 CFR 86.1803. Use as test weight for heavy-duty vehicles at 40 CFR 1066.805.

torque and power, and reinforcing driveline components to handle the additional torque. There is modest consideration for payload increases when considering increases to towing capacity. With a rear ball hitch, the payload increase (referred to as the tongue weight) is approximately 10 percent of the towing capacity increase.¹⁷¹ An alternative towing configuration called a 5th wheel places the trailer mounting point above or slightly in front of the rear axle rather than behind the vehicle. With 5th wheel trailers, the payload increase (referred to as the king pin weight) is approximately 15 percent of the towing capacity increase.¹⁷² This larger increase results because the 5th wheel more evenly distributes a trailer's payload between the front and rear axles; however, 5th wheel towing is not common in light-duty vehicles, and typically requires a pickup truck body to be supported.

In addition to the more expansive design considerations, towing capacity is a more effective means of providing cargo-transporting utility. For example, the highest payload capacity in the LDWF Analysis Fleet is less than 2,000 pounds, compared to the highest towing capacity of 10,000 pounds. In addition, the range of payload capacity across the entire LDWF Analysis Fleet spans less than 1,200 pounds compared to a 10,000-pound spread in towing capacity. Though the HDPUV fuel efficiency program places additional weighting on payload to consider the ALVW test weight, the LDWF recognizes the more significant utility inherent to towing and the more extensive design considerations required for towing. However, because maximum payload values are relatively small compared to TWR values, the percent change of increasing either by equal amounts is significantly higher for payload. For example, if a vehicle had a 1,600-pound maximum payload capacity and a 5,000-pound TWR, increasing each by 100 pounds would constitute a 6.25 percent increase in payload capacity and only a 2.0 percent increase in towing capacity. NHTSA evaluated a range of weighting values for the final rule, ultimately determining that by placing equal weighting on payload capacity and TWR when calculating the LDWF, NHTSA is effectively placing higher significance on TWR, while still providing a significant contribution from payload. Because both LDWF input parameters are weighted equally, the formula can be simplified to the sum of the payload capacity and TWR. The resulting formula for calculating LDWF then becomes:

Equation 2-9: Light-Duty Work Factor General Formula

$$\text{LDWF} = [\text{Payload Capacity}] + [\text{Trailer Weight Rating}],$$

where Payload Capacity is calculated according to Equation 2-7 and Trailer Weight Rating is determined according to SAE J2807. Further discussion can be found in Section VI of the final rule preamble.

2.7.2.3.4. Setting the Light-Duty Work Factor Threshold

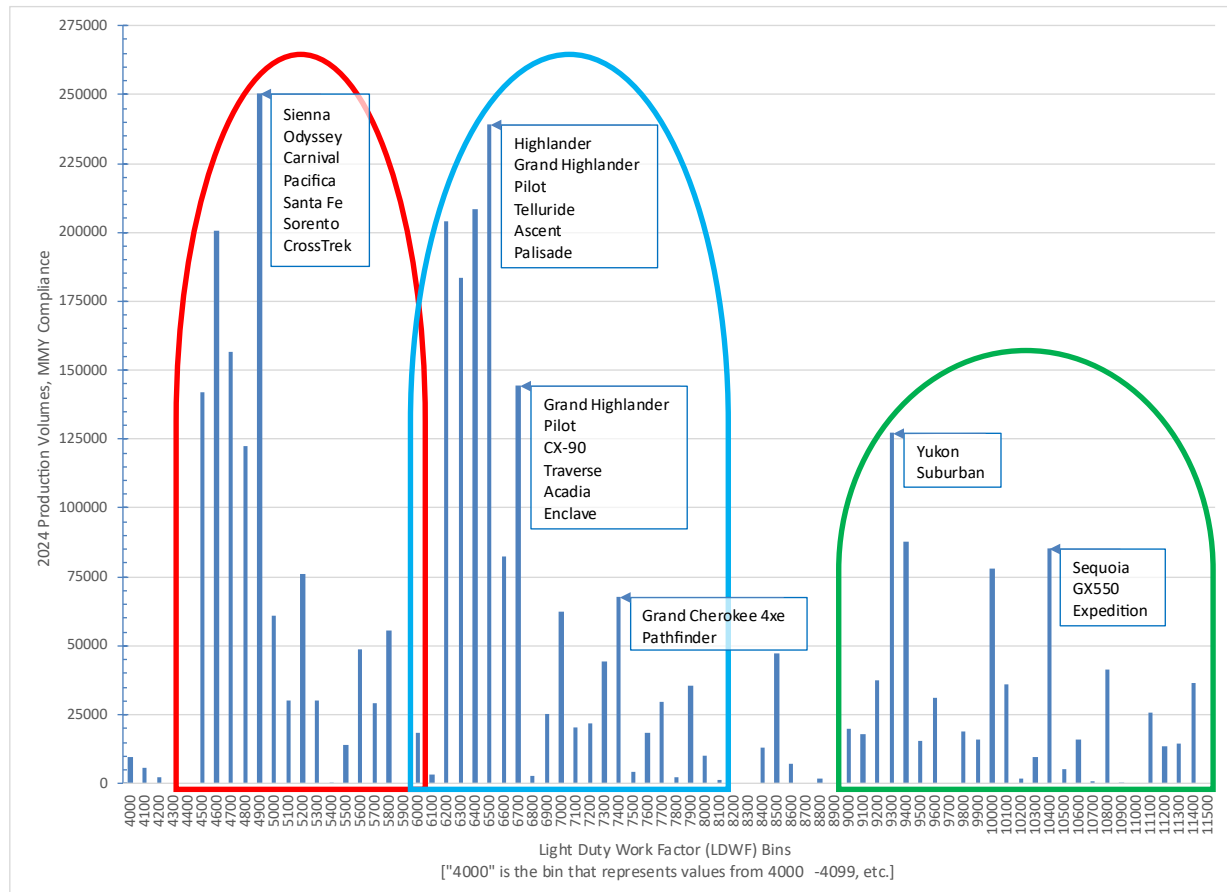
NHTSA then applied the LDWF formula shown in Equation 2-9 to the LDWF Analysis Fleet. To visualize the result, the LDWFs of each vehicle were assigned to bins in increments of 100 ranging from 4000 to 11500, where the 4000 LDWF bin includes the production volume of all vehicles in the analysis

¹⁷¹ SAE International Recommended Practice, Performance Requirements for Determining Tow-Vehicle Gross Combination Weight Rating and Trailer Weight Rating, SAE Standard J2807_202411, Reaffirmed Nov. 2024, last Revised Feb. 2020, Issued Apr. 2008, Section 4.4.2.4. available at: https://doi.org/10.4271/J2807_202411 (accessed: May 25, 2026).

¹⁷² SAE International Recommended Practice, Performance Requirements for Determining Tow-Vehicle Gross Combination Weight Rating and Trailer Weight Rating, SAE Standard J2807_202411, Reaffirmed Nov. 2024, last Revised Feb. 2020, Issued Apr. 2008, Section 4.4.2.5. available at: https://doi.org/10.4271/J2807_202411 (accessed: May 25, 2026).

fleet with a LDWF between 4000 and 4099.¹⁷³ Figure 2-15 shows this visualization.¹⁷⁴ The visualized data resulted in three groupings of production volumes along the x-axis. These groupings have been outlined, along with some of the nameplates represented in select histogram bars found within each grouping.¹⁷⁵ The nameplates have been added to give readers context for understanding the visual; NHTSA's determination was made inclusive only of objective analysis of the anonymous data.

Figure 2-15: Production Volumes by LDWF



To further the threshold analysis and to ascertain how to handle the vehicle population in the 8200-8900 range, NHTSA performed a survival analysis on the LDWF Analysis Fleet based on towing capacity. This analysis seeks to ascertain the probability that a vehicle would meet a range of LDWF thresholds given its towing capacity based on the LDWF Analysis Fleet makeup. This survival analysis (also called a logistic regression or logit model) first takes a binary LDWF pass/fail input for each vehicle line,¹⁷⁶ and then fits a probability curve based on TWR to the resulting pass/fail data. The equation for this curve takes the form:

¹⁷³ Out of 6.6M vehicle production volume in the LDWF Analysis Fleet, 47 percent had a LDWF calculated according to Equation 2-9 of less than 4000. These vehicles are typically limited to between 0- and 2500-pounds of towing capability, and are therefore not shown in the figure.

¹⁷⁴ See Non-Passenger_FRM_Analysis.xlsx, which can be found in the rulemaking docket (NHTSA-2025-0491) by filtering in tab LDWF_Analysis for data and tab LDWF Histogram for figure.

¹⁷⁵ Note that some nameplates can exist across several histogram bars due to differences in configuration, powertrain, trim, packages, etc.

¹⁷⁶ A vehicle line used in the context of this section is defined as a distinct towing and payload combination in the LDWF Analysis Fleet.

Equation 2-10: Logistic Regression General Sigmoid Function

$$P(t) = \frac{I}{1 + e^{-(\beta_0 + \beta_1 t)}}$$

Where:

P = Probability as a function of (t)

t = Trailer weight rating

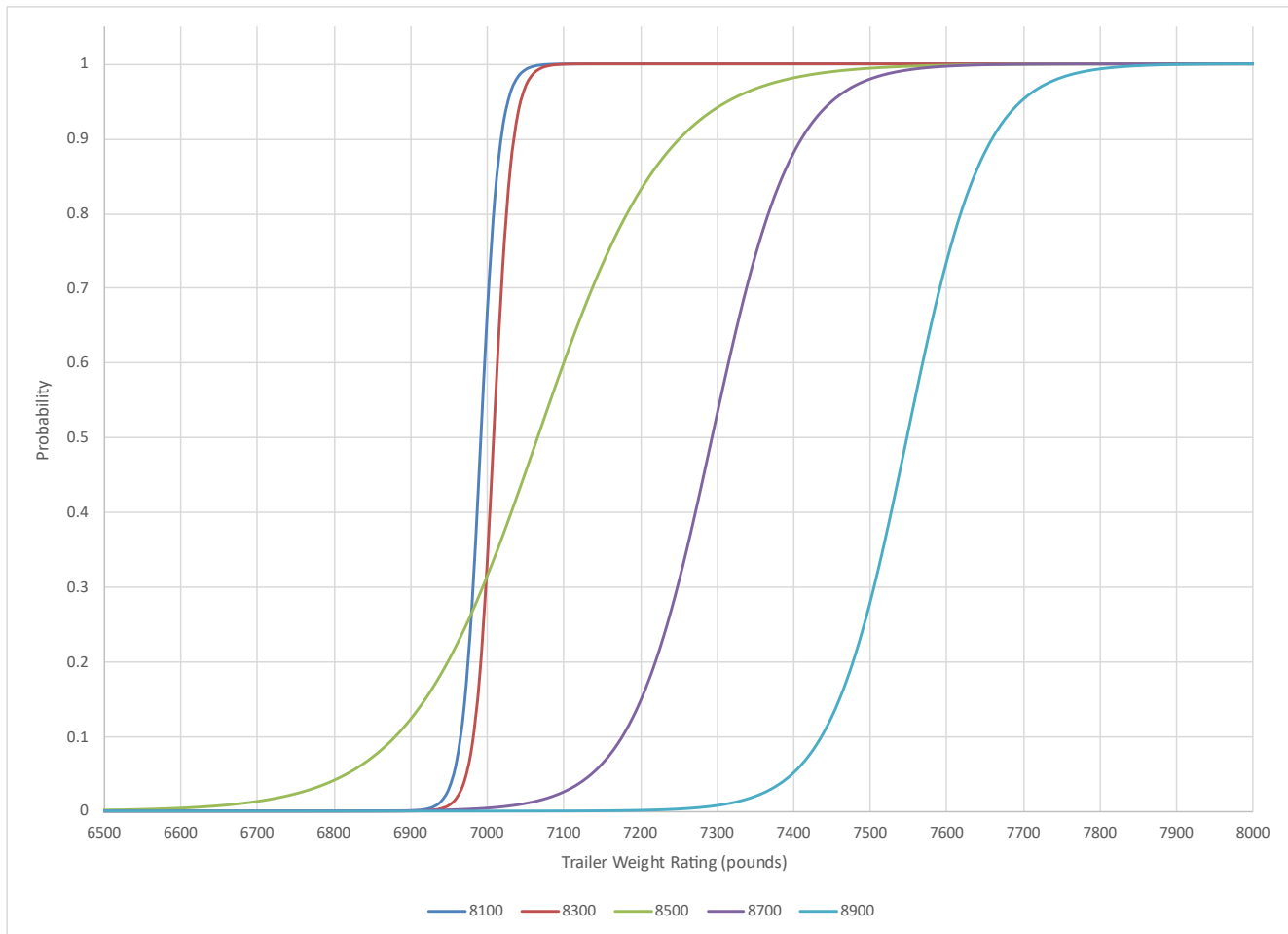
β_0 = Intercept coefficient

β_1 = Rate coefficient

The coefficients are determined using a smooth, non-linear optimization procedure to identify values that maximize the sum of the log likelihoods across the entire LDWF Analysis Fleet relative to the function output. In other words, the coefficients are set by the LDWF Analysis Fleet such that the assigned curve minimizes the cumulative distance between the curve and any pass/fail point from the LDWF Analysis Fleet. Based on the location of the groupings in the preceding histogram, NHTSA performed the logistic regression at LDWFs of 8100, 8300, 8500, 8700, and 8900. The resulting plot is shown in Figure 2-16 below.¹⁷⁷

¹⁷⁷ See Non-Passenger_FRM_Analysis.xlsx, which can be found in the rulemaking docket (NHTSA-2025-0491) by filtering in tab LDWF_Analysis for data and tab TWR Survival Analysis for figure.

Figure 2-16: Binary Logit Probability of Achieving Select LDWF Thresholds Based on Towing Capacity of Vehicle Lines in the 2024 Analysis Fleet



The steepness of each curve shows how reliably a vehicle line from the LDWF Analysis Fleet’s TWR predicts the probability that its LDWF will exceed a given threshold. For example, in the cases of the steep curves corresponding to LDWF thresholds of 8100 (dark blue) and 8300 (red), the LDWFs can be predicted almost independent of payload; towing alone is a nearly perfect predictor of meeting the respective thresholds given the towing and payload makeup of the LDWF Analysis Fleet. In contrast, the relative lack of steepness in the other three curves indicates that manufacturers are already achieving—and could presumably continue to achieve—the finalized LDWF with existing manufacturing materials, techniques, and equipment over a range of payload and towing combinations. The 8500 curve (green) represents the largest range of TWR where meeting the LDWF absent payload capacity information could not be determined with certainty.

In addition to the steepness of the curves, NHTSA also looked at which curve(s) accurately predict physical constraints not explicitly provided to the model. For example, the 8100 curve (dark blue) departs 0-percent probability at approximately 6,950 pounds TWR, indicating that approximately 1,150 pounds of payload capacity would be required to have a non-zero probability of achieving the 8100 LDWF. In the LDWF Analysis Fleet, 78 percent of the vehicle lines used for this regression have a payload capacity greater than 1,150 pounds, indicating that this curve is a poor proxy for the physical constraints observed within the fleet. Conversely, where the 8500-curve (green) departs from 0-percent probability (~6,600 pounds) is approximately the mathematical constraint of the LDWF expressed in Equation 2-9 on the required towing capacity at top 1 percent of payload capacities currently observed in the LDWF Analysis

Fleet’s vehicle lines.¹⁷⁸ The towing capacity at which that same curve reaches 100-percent probability (~7,500 pounds) is approximately the towing capacity that would be required to meet Equation 2-9 while providing just enough payload capacity to support the trailer tongue weight and a driver.¹⁷⁹ In other words, the 8500-curve accurately predicts that any vehicle in the LDWF Analysis Fleet with a towing capacity less than 6,600 pounds would be extremely unlikely to offer sufficient payload capacity to meet a LDWF threshold of 8500, while a vehicle with a TWR greater than 7,500 pounds would likely meet an 8500 threshold, even if it offered minimal payload capacity. These constraints were not explicitly provided to the logit model. Though the 8700 curve (purple) and 8900 curve (blue) outperform the 8100 curve (dark blue) and 8300 curve (red) in the accuracy of their fleet predictions, they are all outperformed by the 8500 curve (green).

These probability curves are based on observed data from the 2024 analysis fleet and do not impose any restriction on future fleets. In other words, just because a particular probability is determined from the 2024 fleet does not imply that future fleets would adhere to that same probability. Given the production volume histogram and vehicle line logarithmic regression data, NHTSA determines that 8500 is an appropriate threshold for the LDWF.

Equation 2-11: LDWF Threshold Formula

$$[\text{Payload Capacity}] + [\text{Trailer Weight Rating}] \geq 8500$$

There is no restriction on manufacturers opting to make significant changes to payload and towing utility to qualify as non-passenger vehicles via the LDWF pathway in future regulatory years. Conversely, there is also no restriction on manufacturers opting to de-content payload and towing to potentially improve their performance in the passenger automobile fleets.

2.7.2.3.5. *Non-Passenger Fleet Impact of the Light-Duty Work Factor*

Unlike the finalized changes described in Final TSD Chapters 2.7.2.1 and 2.7.2.2, which would remove or restrict existing non-passenger automobile pathways, the LDWF introduces a new, currently unavailable pathway into the non-passenger automobile fleet. As previously discussed, applying the changes finalized in Final TSD Chapters 2.7.2.1 and 2.7.2.2 results in 6.4M MY 2024 vehicles being moved to the passenger fleet. Adding the finalized LDWF qualification pathway to these two finalized changes reduces the number of MY 2024 vehicles moved to the passenger automobile fleet to 5.6M.

2.7.3. Domestic versus Import Passenger Fleet Allocation

To determine compliance with NHTSA’s fuel economy standards, the passenger automobile fleet is further separated into two compliance categories: domestic passenger automobiles and import passenger automobiles. This designation is self-assessed and self-reported by the manufacturers based on component origin, subassembly location, and final assembly location in accordance with the statute and EPA’s regulations.^{180,181} As there is no such designation within the non-passenger automobile fleet, and therefore, no information about the percent manufacturing cost attributable to value added domestically (which includes Canada and Mexico), NHTSA had to rely on other data sources, including publicly

¹⁷⁸ Using Equation 2-9: [LDWF] – [TWR at Departure from 0 percent probability]=[Payload] becomes 8500-6600=1900.

¹⁷⁹ From Equation 2-9: [LDWF] – [TWR at Arrival to 100 percent probability]=[Minimum Payload] becomes 8500-7500=1000 lbs., of which 750 lbs. is required for tongue weight.

¹⁸⁰ 49 U.S.C. 32904(b).

¹⁸¹ 40 CFR 600.511-08.

available data, engineering judgement, and data provided by manufacturer’s in the NPRM comment response period to assign reclassified automobiles to the domestic passenger automobile and import passenger automobile compliance categories.

To reclassify the non-passenger vehicles that would move to the passenger automobile fleet as a result of regulatory vehicle classification changes, NHTSA needed to determine which passenger automobile subfleet each non-passenger automobile nameplate would likely be assigned. To do this, NHTSA used the AALA data for MY 2024 to determine the percentage of the value of parts that originate in the United States or Canada for each nameplate in the non-passenger automobile fleet.^{182,183} Though there is no single percentage of the value of parts that makes a nameplate a domestic passenger automobile, NHTSA assumed that 75 percent or more of United States/Canadian origin would likely be assigned a domestic car by manufacturers.¹⁸⁴

In lieu of data from manufacturers on how the non-passenger automobiles may be assigned in the passenger automobile fleet, any nameplate that had 75 percent or more parts content between the United States and Canada was assigned to the domestic car fleet. Any nameplate that had less than 75 percent was assigned to the import car fleet. If a nameplate that moved from the non-passenger to passenger automobile fleet had less than 75 percent of its content between the United States and Canada, it was given an import car fleet assignment. To help improve the accuracy of the fleet assignments, if a nameplate had another variant of the nameplate in the passenger automobile fleet, the non-passenger automobile variant moving to the passenger automobile fleet would be given the same fleet assignment as its passenger automobile variant. For example, if a vehicle shares a chassis with a vehicle or is an all-wheel drive (AWD) variant of a front-wheel drive (FWD) vehicle that resides in the passenger fleet, NHTSA used that vehicle’s domestic or import designation to infer the appropriate designation for the vehicle being reclassified to the passenger automobile fleet.

NHTSA emphasizes that the subfleet designation has no impact on the curve-setting analysis described in Final TSD Chapter 1, as the curve is based on the entire composition of the passenger automobile fleet. However, the classification of a vehicle as being domestically produced is necessary for NHTSA’s analysis of the impacts of the minimum domestic passenger car standard (MDPCS).¹⁸⁵ Preamble Section VI contains further discussion on the domestic and import fleets.

2.7.4. Fleet Comparison of Current Classification versus Reclassification

Table 2-12 and Table 2-13 show the current classification and reclassification pathways in plain-text descriptions of their chief characteristics:

Table 2-12: Current Classification Non-Passenger Characteristics

	Chief Non-Passenger Characteristics (At least one required for non-passenger classification)
1	Primarily transports more than 10 individuals
2	Provides temporary living quarters
3	Transports property on an open bed

¹⁸² 49 CFR part 583, Automobile Parts Content Labeling (1994).

¹⁸³ The American Automobile Labeling Act Master Sheet for MY 2024 is available at <https://www.nhtsa.gov/sites/nhtsa.gov/files/2024-06/MY2024-AALA-Alphabetical-6-3-24.pdf>.

¹⁸⁴ 49 CFR part 583.

¹⁸⁵ 49 U.S.C. 32902(b)(4).

4	Provides, as sold to the first retail purchaser, greater cargo-carrying than passenger-carrying volume		
5	Permits expanded use of the automobile for cargo-carrying purposes or other non-passenger-carrying purposes		
6	Has a rated gross vehicle weight (GVW) greater than 6,000 lbs.	AND	Meets four out of five of: - An approach angle equal to or greater than 28 degrees - A break over angle equal to or greater than 14 degrees - A departure angle equal to or greater than 20 degrees - A running clearance of equal to or greater than 20 cm - A front and rear axle clearance of equal to or greater than 18 cm
	OR		
	Has 4-wheel drive		

Table 2-13: Reclassification Non-Passenger Characteristics

	Chief Non-Passenger Characteristics (At least one required for non-passenger classification)		
1	Primarily transports more than 10 individuals		
2	Provides temporary living quarters		
3	Transports property on an open bed		
4	Provides, as sold to the first retail purchaser, greater cargo-carrying than passenger-carrying volume		
5	Meets the light-duty work factory such that: $[Payload\ Capacity] + [Trailer\ Weight\ Rating] \geq 8500$		
6	Has a rated GVW greater than 6,000 lbs.	AND	Meets all four of: - An approach angle equal to or greater than 28 degrees - A break over angle equal to or greater than 14 degrees - A departure angle equal to or greater than 20 degrees - A running clearance of equal to or greater than 20 cm
	OR		
	Has 4-wheel drive		

Applying all of the finalized changes described in Final TSD Chapter 2.7.2 and assigning passenger vehicles to the appropriate fleet described in Final TSD Chapter 2.7.3 results in the following changes to the MY 2024 fleet compositions. Note that these values:

- Reflect the dedicated vehicle omission described in Final TSD Chapter 2.7.1.
- Represent changes to the MY 2024 baseline fleet for use as inputs to the fuel economy footprint-based curve setting analysis and CAFE Model reclassification input.
- Do not impact CAFE compliance or vehicle classification until MY 2030.

Table 2-14: Reclassification Changes in Quantities and Fleet Percentages within Light-Duty

Fleet	Non-Passenger Automobile		Domestic Car		Import Car	
	Quantity	Percentage	Quantity	Percentage	Quantity	Percentage
Current	9.3M	67.9%	2.0M	14.7%	2.4M	17.3%
Reclassified	3.7M	26.8%	3.6M	26.3%	6.4M	47.0%

3. Technology Pathways, Effectiveness, and Cost

Vehicle manufacturers meet fuel economy standards by applying additional fuel-economy-improving technologies to their vehicles. To assess what increases in fuel economy standards may be achievable and at what cost, NHTSA first needs accurate characterizations of fuel-economy-improving technologies. NHTSA collected data on over 50 fuel-economy-improving technologies available for manufacturers to apply to their light-duty vehicles in response to fuel economy standards. NHTSA’s review also includes determining technology effectiveness values, technology costs, and how NHTSA realistically expects manufacturers might apply the technologies in the rulemaking timeframe. The characterization of these technologies, technology effectiveness values, and technology cost assumptions build on work from DOT, EPA, National Academies of Sciences, Engineering, and Medicine (NASEM), and other Federal and State government agencies, including Argonne.

After spending more than a decade refining the technology pathways, effectiveness, and cost assumptions used in successive CAFE Model analyses, NHTSA has developed guiding principles to ensure that the CAFE Model’s simulation of manufacturer compliance pathways results in impacts that NHTSA would reasonably expect to see in the real world. These guiding principles are as follows:

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. NHTSA expects 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 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. NHTSA uses the term “vehicle type” in the CAFE analysis to refer to 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 the vehicles, the effectiveness improvement for adding the technology will differ.

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

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 demonstrate better performance and lower costs than the modeled systems, while some may demonstrate poorer performance and higher costs. However, employing this representative approach ensures 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 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. Providing a consistent reference point to measure incremental technology effectiveness values ensures NHTSA captures accurate effectiveness values for each technology combination.

The following subchapters discuss the engine, transmission, hybridization, mass reduction, aerodynamic, tire rolling resistance, and other vehicle technologies considered in this analysis. The following subchapters discuss:

- How NHTSA defines the technology in the CAFE Model,¹⁸⁶
- How NHTSA assigns 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 subchapters 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, which are installed as part of the CAFE Model Executable File and not included in the input/output folders. NHTSA shows technology effectiveness charts for each technology type. The effectiveness values reflect the application of 49 U.S.C. 32902 constraints: specifically, PHEV technologies only show the effectiveness achieved when operating in a gasoline-only mode (charge sustaining mode). Similarly, the technology costs provided in each subchapter are *examples* of absolute costs seen in specific model years, for specific vehicle technology 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

ICEs convert the chemical energy in fuel into useful mechanical power. 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 interaction between these fluids and the mechanical

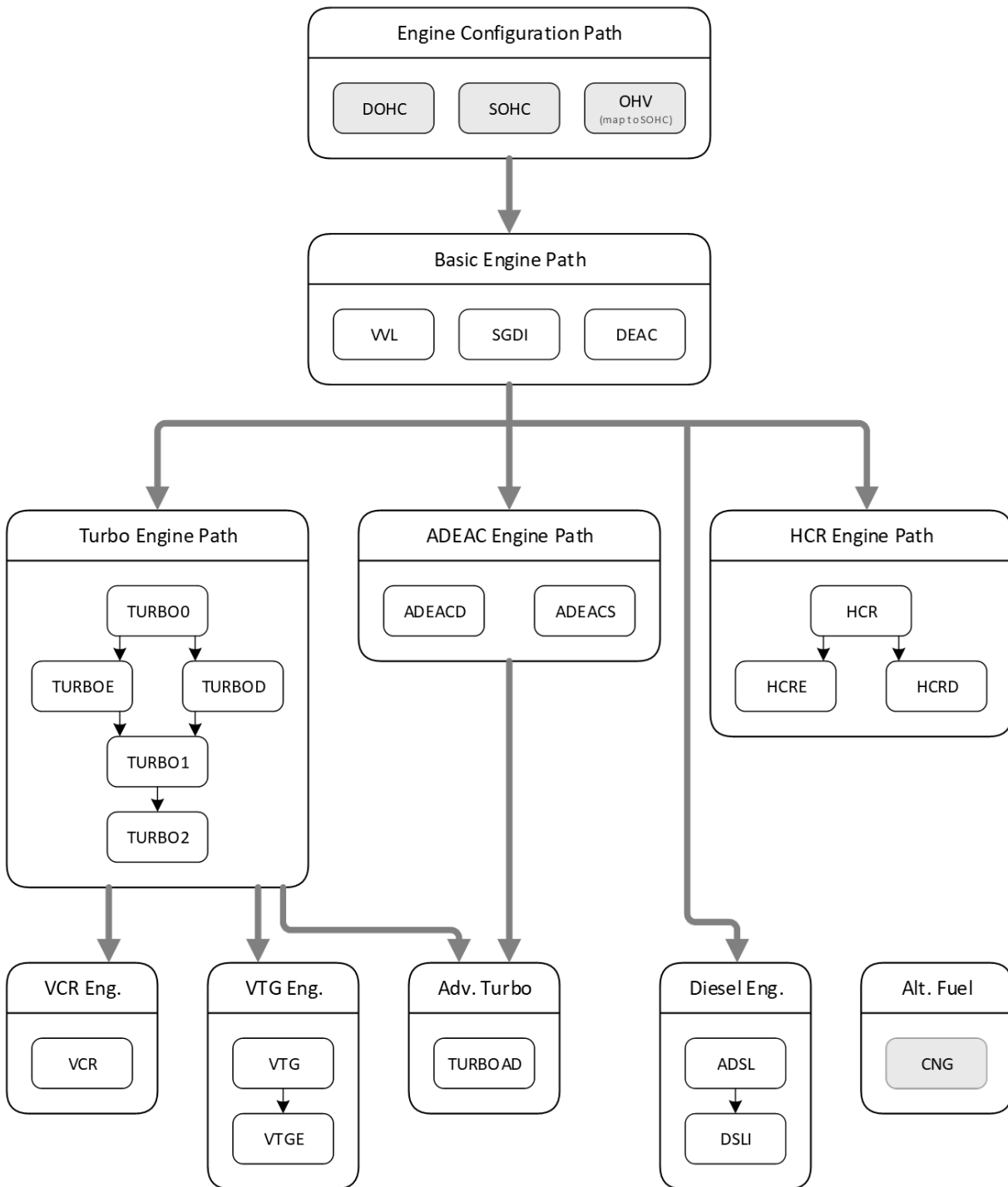
¹⁸⁶ Note: Due to the diversity of definitions industry sometimes employs for technology terms, or in describing the specific application of technology, the terms defined here may differ from how the technology is defined in the industry.

components of the engine.¹⁸⁷ The mechanical power that is generated is used to perform useful work, such as vehicle propulsion.

For this analysis, the extensive variety of light-duty 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. NHTSA does not include technologies that are unlikely to be feasible in the rulemaking timeframe, technologies unlikely to be compatible with U.S. fuels, technologies for which there was not appropriate data available to allow the simulation of effectiveness across all vehicle technology classes in this analysis, or technologies the law prohibits from consideration in setting fuel economy standards. The technology paths for light-duty engines can be seen in Figure 3-1.

¹⁸⁷ Heywood, J. B., *Internal Combustion Engine Fundamentals*, Columbus, OH: McGraw-Hill Education, Chapter 1 (2018), available at: <https://www.accessengineeringlibrary.com/content/book/9781260116106> (accessed: May 25, 2026) (hereinafter, “Heywood 2018”).

Figure 3-1: LD Engine Technology Paths Available



The following subchapter discusses how NHTSA defines ICE technologies considered in this analysis. NHTSA describes the CAFE Model’s general engine technology categories and discusses the engine technologies’ relative effectiveness. NHTSA also reviews how the categories are assigned to the MY 2024 light-duty analysis fleet, as well as the engine paths’ adoption features. Finally, NHTSA provides 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 light-duty vehicles. 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, NHTSA divides engine technologies into two categories: “basic engine technologies” and “advanced engine technologies.” “Basic engine technologies” refer to technologies that can be adopted by 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 cost and effectiveness values.

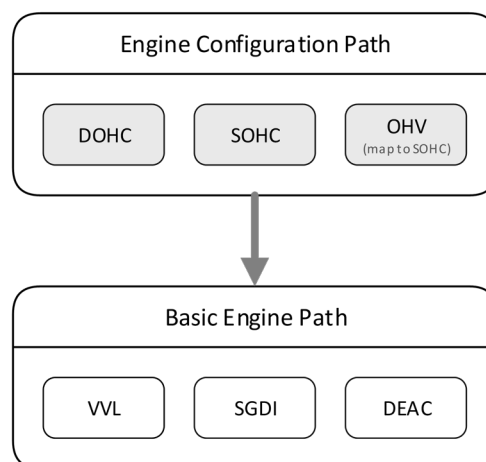
The light-duty engine technology pathways applied in the CAFE Model have been selected and refined over a period of more than ten years, based on engines in the market, stakeholder comments, and engineering judgment—subject to factors listed above, including technologies most likely available during the rulemaking timeframe 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, technologies for which there was not appropriate data available to allow the simulation of effectiveness across all vehicle technology classes in this analysis, or technologies the law prohibits NHTSA from considering when setting fuel economy standards.

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 cylinder deactivation (DEAC). Cylinder deactivation includes a basic level (DEAC) and an advanced level (ADEAC). For this analysis, VVT technology is inherently integrated into all spark ignition (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: DOHC engine architecture and single overhead camshaft (SOHC) engine architecture. A third architecture exists, OHVs, where the camshaft is not mounted overhead. NHTSA mapped engines with this architecture to SOHC engines. Figure 3-2 shows the light-duty basic engine technologies.

Figure 3-2: LD Basic Engine Technologies 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 enhance efficiency further.¹⁸⁸ 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 CR, 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.¹⁸⁹ 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 MY 2024 light-duty analysis fleet.

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 either an increase in CR, more optimal spark timing for improved efficiency, or both.¹⁹⁰ SGDI is common in the light-duty MY 2024 fleet. 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.¹⁹¹ The engine runs temporarily as though it were a smaller engine, reducing pumping losses and improving efficiency. DEAC is present in the 2024 light-duty analysis fleet.

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.¹⁹² The basic engine technologies that can be applied to DOHC engines for the light-duty analysis include VVL, SGDI, and DEAC. To represent the possible configurations of basic engine technologies in the analysis, NHTSA developed engine fuel map models

¹⁸⁸ National Research Council, Cost, Effectiveness, and Deployment of Fuel Economy Technologies for Light-Duty Vehicles, Washington, D.C.: The National Academies Press, p. 31 (2015), available at: <https://nap.nationalacademies.org/catalog/21744/cost-effectiveness-and-deployment-of-fuel-economytechnologies-for-light-duty-vehicles> (accessed: May 25, 2026). (hereinafter, “2015 NAS report”).

¹⁸⁹ 2015 NAS report, at p. 32.

¹⁹⁰ 2015 NAS report, at p. 34.

¹⁹¹ 2015 NAS report, at p. 33.

¹⁹² 2015 NAS report, at p. 31.

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 MY 2024 analysis 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 10.2
Eng02	DOHC+VVL	VVL added to Eng01
Eng03	DOHC+VVL+SGDI	SGDI added to Eng02, compression ratio 11
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.¹⁹³ The basic engine technologies that can be applied to SOHC engines for the light-duty analysis include VVL, SGDI, and DEAC. Like DOHC engines, engine map models for SOHC engines use an incremental improvement approach. The SOHC engine map models are based on Eng01 with the removal of one camshaft. NHTSA included SOHC VVT Eng5a in previous analyses but did not include it for this analysis. NHTSA found that the Eng5a map model’s internal friction, inherited from the DOHC engine on which it was based, 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). SOHC engines are not common in the light-duty MY 2024 analysis fleet. In the light-duty analysis, vehicles assigned OHV are mapped to SOHC engines. Table 3-2 shows the light-duty SOHC engine map models. Chapter 3.1.4.1.1 discusses how NHTSA 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 3-3 shows the additional SOHC technology combinations with performance values drawn from alternative engine map models.

¹⁹³ 2015 NAS report, at p. 31.

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: Light-Duty SOHC Emulated Engines from Analogous Models

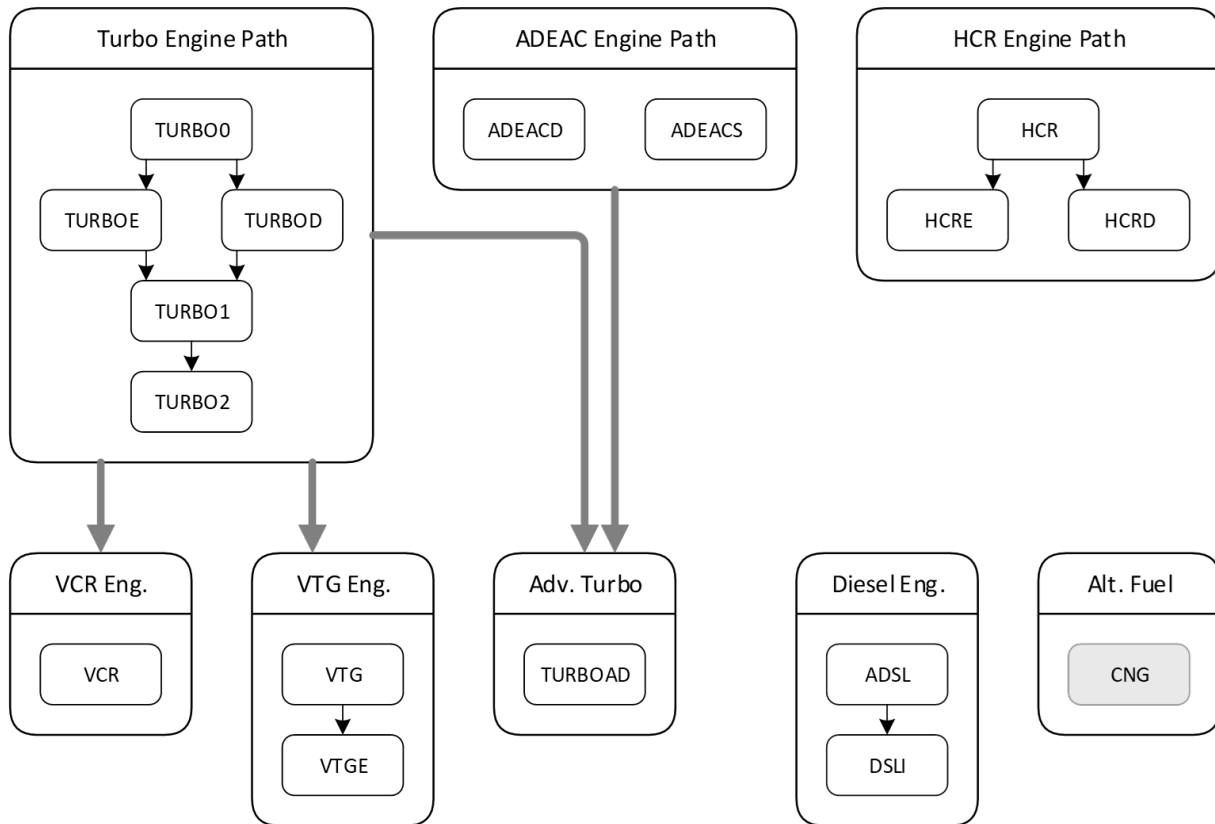
Engine Performance is Based on	Technologies	Notes
Eng18	SOHC+SGDI	See Chapter 3.1.4 for effectiveness discussion
Eng19	SOHC+DEAC	See Chapter 3.1.4 for effectiveness discussion
Eng20	SOHC+VVL+DEAC	See Chapter 3.1.4 for effectiveness discussion
Eng21	SOHC+SGDI+DEAC	See Chapter 3.1.4 for effectiveness discussion

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 3-3 shows the advanced technology paths for this analysis.

Figure 3-3: The Light-Duty Advanced Engine Technology Paths



3.1.1.2.1. Advanced Cylinder Deactivation Engines

Advanced cylinder deactivation (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 MY 2024 light-duty analysis fleet.

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.¹⁹⁴

Cooled exhaust gas recirculation (CEGR) is also part of the advanced forced induction technology path and is in addition to iEGR discussed earlier. CEGR is another method for diluting the incoming air that

¹⁹⁴ 2015 NAS report, at p. 34.

takes exhaust gases, passes them through a heat exchanger to reduce their temperature, and then mixes them with incoming air in the intake manifold.¹⁹⁵ 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: reference baseline turbocharged downsized technology (TURBO0), turbocharged engine with cooled exhausted recirculation (TURBOE), turbocharged engine with DEAC (TURBOD), turbocharged engine with advanced cylinder deactivation (TURBOAD), turbocharged downsized technology (TURBO1), and TURBO2. See Table 3-4 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.

Both TURBOE and TURBOD are defined by the application of their respective technologies, CEGR 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 3-4.

¹⁹⁵ 2015 NAS report, at p. 35.

Table 3-4: 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 exhaust gas recirculation (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

3.1.1.2.3. High Compression Ratio and Atkinson Engines

In this analysis, HCR engines represent a class of SI engines that achieve a higher level of fuel efficiency by implementing a high geometric CR with varying degrees of late intake valve closing (LIVC) and without the use of an electric drive motor.^{196,197} These engines operate on a modified Atkinson cycle allowing for improved fuel efficiency under certain conditions, but still offering enough power not to require an electric machine; 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 used only in HEVs (see Chapter 3.1.1.2.3.2).

Historically, the Otto combustion cycle has been used by most gasoline-based SI engines.¹⁹⁸ 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 CR, thereby maximizing efficiency, and make use of an electric machine to supplement the loss in power density.^{199,200} The main principles behind the Atkinson cycle are over-expansion of the combustion gases

¹⁹⁶ LIVC is a method that 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.

¹⁹⁷ See the 2015 NAS report, Appendix D, for a short discussion on thermodynamic engine cycles.

¹⁹⁸ Otto cycle is a 4-stroke cycle that has four piston movements over two engine revolutions for each cycle. First stroke: intake or induction; second stroke: compression; third stroke: expansion or power stroke; and finally, fourth stroke: exhaust.

¹⁹⁹ Yamaji, K. *et al.*, New 2.0L I4 Gasoline Direct Injection Engine With Toyota New Global Architecture Concept, SAE Technical Paper 2018-01-0370, Warrendale, PA: SAE International (2018), available at: <https://doi.org/10.4271/2018-01-0370> (accessed: May 25, 2026).

²⁰⁰ Feng, R. *et al.*, Investigations of Atkinson Cycle Converted From Conventional Otto Cycle Gasoline Engine, SAE Technical Paper 2016-01-0680, Warrendale, VA: SAE International (2016), available at: <https://www.sae.org/papers/investigations-atkinson-cycle-converted-conventional-otto-cycle-gasoline-engine-2016-01-0680> (accessed: May 25, 2026).

and reduced pumping losses. The gases 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 gases allows more work to be extracted from the combustion process, resulting in improved fuel efficiency.^{201,202}

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.²⁰³ It is important to note that in both cases, the geometric CR of the engine will be different (higher) than the actual, or effective, CR of the engine.^{204,205}

One major disadvantage of the Atkinson cycle is a significant reduction in power density.^{206,207} 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, as in the Toyota Prius, or in conjunction with road load reducing technologies that reduce the need for engine power to maintain vehicle performance.^{208,209}

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, NHTSA defines HCR engines as being naturally aspirated, gasoline-fueled, spark ignited, and able to apply various levels of LIVC dynamically based on load demand using a geometric CR of 12.5:1 or greater.²¹⁰ An HCR engine uses less fuel for each engine cycle, which increases fuel

²⁰¹ Compression ratio is the ratio of the maximum to minimum volume in the cylinder of an ICE.

²⁰² 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).

²⁰³ Heywood 2018, Chapter 5.

²⁰⁴ 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.

²⁰⁵ 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.

²⁰⁶ Power density is the engine power per unit of displacement (= [Engine Power]/[Engine Displacement]).

²⁰⁷ Heywood 2018, Chapter 5.

²⁰⁸ Toyota, Under the Hood of the All-new Toyota Prius, last revised: Oct. 13, 2015, available at: <https://global.toyota/en/detail/9827044> (accessed: May 25, 2026).

²⁰⁹ Road load reducing technologies include rolling resistance reduction technologies, vehicle mass reduction, and aerodynamic drag reduction.

²¹⁰ 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 the analysis; as discussed in the section on engine assignments below, NHTSA looks at a number of factors to perform baseline engine assignments.

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 CR, reducing over-expansion, and sacrificing efficiency for increased power density.²¹¹ However, there is a limit to how much air-fuel mixture can remain in the compression chamber of an HCR engine because over-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 CR, 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 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.

“Lower power density issues” translate to a low torque density,²¹² 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 a particular engine design to be used in conditions 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),²¹³ 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.²¹⁴

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.^{215,216} As vehicles require higher payloads and towing capacities,²¹⁷ 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

²¹¹ Variable valve actuation is a general term used to describe any single or combination of VVT, VVL, and Variable Valve Duration used to alter an engine’s valvetrain dynamically during operation.

²¹² Torque = radius x force.

²¹³ But see the 2024 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 NHTSA does not believe manufacturers will increase the displacement of HCR engines to make the necessary power.

²¹⁴ See Toyota, 2024 Toyota Tacoma Makes Debut on the Big Island, Hawaii, last revised: May 19, 2023, available at: <https://pressroom.toyota.com/2024-toyota-tacoma-makes-debut-on-the-big-island-hawaii/> (accessed: May 25, 2026).

²¹⁵ 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 p. 6.

²¹⁶ Feng, R. *et al.*, Investigations of Atkinson Cycle Converted From Conventional Otto Cycle Gasoline Engine, SAE Technical Paper 2016-01-0680, Warrendale, VA: SAE International (2016), available at: <https://www.sae.org/papers/investigations-atkinson-cycle-converted-conventional-otto-cycle-gasoline-engine-2016-01-0680> (accessed: May 25, 2026).

²¹⁷ See Tucker, S., What Is Payload: A Complete Guide, Kelly Blue Book, last revised: Feb. 2, 2023, available at: <https://www.kbb.com/car-advice/payload-guide/#link3> (accessed: May 25, 2026) (“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.”).

required, the application of this technology becomes less effective and more limited.²¹⁸ For these reasons, to maintain a performance-neutral analysis, and as discussed further below, NHTSA limits non-hybrid and non-plug-in-hybrid HCR engine application to certain categories of vehicles.²¹⁹

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 CEGR; and, finally, (3) the Atkinson-enabled engine with DEAC (HCRD). A summary of each of the engine technologies is shown in Table 3-5. 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.

Table 3-5: 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 Vehicle Engines

Atkinson engines operate in a full-time Atkinson cycle that incorporates the use of an electric motor to assist in vehicle propulsion. The most common method of achieving Atkinson operation is the use of LIVC. This method allows backflow from the combustion chamber into the intake manifold, reducing the effective CR, 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 electric motors and significantly reducing road loads can compensate for the lower power density and maintain desired performance levels for the vehicle.²²⁰

²¹⁸ 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 pickup 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.”).

²¹⁹ To maintain performance neutrality when sizing powertrains and selecting technologies NHTSA performs a series of simulations in Autonomie that 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.2.c (titled “Technology Effectiveness Values”) of the final rule preamble, and additional reasons why NHTSA maintains a performance-neutral analysis are discussed in Section II.C.2.f (titled “Technology Applicability Equations and Rules”) of the final rule preamble.

²²⁰ Toyota, Under the Hood of the All-new Toyota Prius, last revised: Oct. 13, 2015, available at: <https://global.toyota/en/detail/9827044> (accessed: May 25, 2026).

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.²²¹

Table 3-6: Atkinson Engine Map Model

Engine	Technology	Notes
Eng26	SHEVPS PHEV20PS PHEV50PS	HEV-PHEV Atkinson Cycle Engine 1.8L

The Atkinson engine, Eng26, is used for “power-split” hybrid vehicle architectures. NHTSA also models “parallel,” or P2, architectures for SHEVs and PHEVs. NHTSA allows 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 like 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 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.²²² However, the forced air induction mitigates power density issues and allows for a wider application of the engine technology. Miller cycle-enabled engines may use a variable geometry turbocharger 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.

NHTSA uses two engine map models to represent Miller cycle-enabled engines (see Table 3-7). The basic level Miller cycle-enabled engine includes the application of a variable turbo geometry (VTG) technology. 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 CEGR.²²³

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.²²⁴

²²¹ Matsuo, S. *et al.*, The New Toyota Inline 4 Cylinder 1.8L ESTEC 2ZR-FXE Gasoline Engine for Hybrid Car, SAE Technical Paper 2016-01-0684, Warrendale, PA: SAE International (2016), available at: <https://doi.org/10.4271/2016-01-0684>, (accessed: May 25, 2026).

²²² 2021 NAS report, at Section 4.

²²³ 2015 NAS report, at p. 116.

²²⁴ 2015 NAS report, at p. 62.

Table 3-7: 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 CR 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 4-cylinder, high BMEP (23-27 bar) applications. Nissan is the only manufacturer to use this technology in the MY 2024 analysis fleet.

For this analysis, one engine map model represents the VCR system. See Table 3-8 for more information on the VCR technology.

Table 3-8: 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 CR,²²⁵ and a very lean air/fuel mixture relative to an equivalent-performance gasoline engine.²²⁶ 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.

NHTSA considered two levels of diesel engine technology for the light-duty fleet (see Table 3-9). The basic level diesel engine technology (ADSL) is based off a modern 3.0L turbocharged diesel engine. NHTSA developed a more advanced diesel engine (DSLI) by adding DEAC to the ADSL engine technology.

²²⁵ The diesel cycle is also a 4-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.

²²⁶ See the 2015 NAS report, Appendix D, for a short discussion on thermodynamic engine cycles.

Table 3-9: 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

3.1.1.2.7. *Alternative Fuel Engines*

CNG systems are ICE vehicles that run on natural gas as a fuel source. The fuel storage and supply systems for these engines differ tremendously from gasoline, diesel, and flexible-fuel vehicles.²²⁷ CNG engines are a basic level-only technology and are not applied to any vehicle that did not already include a CNG engine as a baseline engine assignment. The MY 2024 light-duty analysis fleet does not include any dedicated CNG vehicles. Because this is a restricted path in the engine technology tree that no non-CNG vehicle would adopt, no further discussion of CNG is included in this Final TSD chapter as it was not utilized in this analysis.

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.²²⁸ NHTSA built the fleet to capture, as best possible, the current level of these advances and to update market data inputs for the CAFE Model. NHTSA built the light-duty fleet using mid-model year 2024 CAFE compliance data, press releases, vehicle benchmarking studies, technical publications, and CBI. NHTSA uses these sources to ensure the fleet is represented as accurately as possible. For further discussion, see Chapter 2.2.

NHTSA uses data for each manufacturer to determine which platforms share engines. Within each manufacturer's fleet, NHTSA assigns unique identification designations (engine codes) based on configuration, technologies applied, displacement, CR, and power output. NHTSA uses power output to distinguish between engines that might have the same displacement and configuration but significantly different HP ratings.

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 2024 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, NHTSA assigns each engine one unique engine code or assigns an engine multiple codes if there are variants that use different technologies. For example, NHTSA assigns the 2024 Chevrolet Camaro naturally aspirated 6.2L V8 engine one of two engine codes:

²²⁷ Flexible-fuel vehicles are designed to run on gasoline or gasoline-ethanol blends of up to 85 percent ethanol.

²²⁸ EPA, 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.: EPA, pp. 1 – 15 (2023), available at: <https://www.epa.gov/automotive-trends/download-2023-automotive-trends-report-previous-year> (accessed: May 25, 2026) (hereinafter, 2023 EPA Automotive Trends Report).

116202 (gasoline only with cylinder deactivation), and 116204 (gasoline only without cylinder deactivation).²²⁹ All Camaros that use one of these engines will reference the same engine code. NHTSA then assigns 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.

NHTSA represents each engine using engine technologies and engine technology classes. NHTSA assigns 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 above, where one engine map (with the prefix signifier “eng”) is directly related to one or more technologies.

When NHTSA assigns engine technologies in the analysis fleet, NHTSA must look at the *actual* technologies on a manufacturer’s engine and compare those technologies to the engine technologies *in the analysis*, (*i.e.*, specific boxes on the technology tree, represented by a specific engine map). NHTSA has just over 250 unique engine codes in the light-duty analysis fleet. NHTSA engineers identify the technologies present on those unique engines in the real world and make decisions about which of the approximately 30 engine map models (and therefore engine technology on the technology tree) best represent those real-world engines.

When NHTSA looks at how best to fit each of those 350 engines to the 30 engine technologies/engine maps, the agency uses specific technical elements contained in manufacturer publications, press releases, vehicle benchmarking studies, technical publications, manufacturer specification sheets, CBI (like the specific technologies, displacement, CR, and power mentioned above), and engineering judgment. For example, in the light-duty analysis, an engine with a 13.0:1 CR is a good indication that an engine would be considered an HCR engine in the 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, such as some combination of SGDI, increased engine displacement compared to other competitors, a high energy spark system, 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, but more complex engines need data and engineering judgment to be assigned. However, NHTSA believes that the engine mapping captures the fuel-efficient technologies manufacturers have deployed for MY 2024.

NHTSA assigns each individual vehicle’s initial fuel economy value based on CAFE compliance data for that vehicle rather than using these maps. The compliance modeling then 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).

Engine technology classes are a second identifier used in the analysis to 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

²²⁹ Market Data Input File, ‘Vehicles’ Tab, Line 925, 927, Column I.

cam, _ohv for OHV, or blank for dual-overhead cam. Table 3-10 shows examples of observed engines with their corresponding assigned engine technologies.

Table 3-10: 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
General Motor Company (GMC) Acadia	Turbocharged DOHC I4 w/cylinder deactivation	6C2B	TURBOD
Audi RS 3	Turbocharged DOHC I5	6C2B	TURBO2
Bentley Continental GTC	Turbocharged DOHC W12 w/ cylinder deactivation	16C4B	TURBOD
Honda Passport	Naturally Aspirated SOHC V6	6C2B_SOHC	VVL, SGDI, DEAC
Honda Civic	Naturally Aspirated DOHC I4	4C1B_L	VVL, SGDI
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

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 MY 2024 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 an I3 (3C1B) engine architecture. Some instances can be more complex, including low HP variants for 4-cylinder engines, and are shown in Table 3-11. Diesel engines map to engine technology classes that match the observed cylinder count because naturally aspirated diesel engines are not found in new light-duty vehicles in the U.S. market. Table 3-12 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 3-11: LD 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	16	Any	Turbo	16C4B

Table 3-12: 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

Having a large number of modeled technologies allows NHTSA to characterize technologies present on engines in the analysis fleet. This collection of technologies represents the best available information NHTSA has, at the time of this action, regarding both currently available engine technologies and engine technologies that could be feasible for application in the U.S. fleet during the rulemaking timeframe. NHTSA believes 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 still include some 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 hybrids in the CAFE Model. 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 shows the technology paths available for light-duty 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 3-13 provides 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 be assigned only as an initial technology. Technologies applicable only during a platform redesign can be applied during a platform refresh if another vehicle platform that uses the same engine (identified by having the same engine code) has already applied the technology during a redesign first. For example, models of the GMC Acadia and the Chevrolet Traverse use the same engine (represented by engine code 112511 in the Market Data Input File); if the Traverse 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.

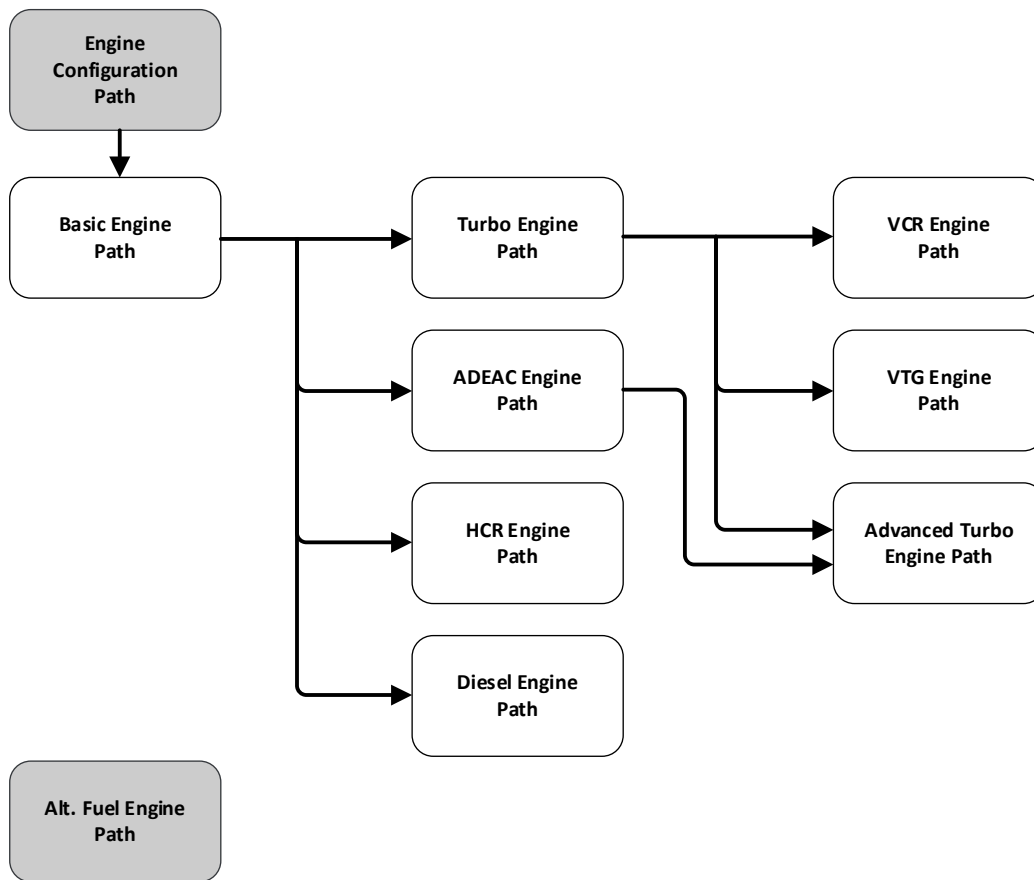
Table 3-13: LD Technology Application Schedule

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

Engine technology adoption also depends on technology path and phase-in caps. Figure 3-4 shows the light-duty flowchart 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.

Figure 3-4: LD Engine Path Flowchart



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. An engine can jump from the Basic Engine 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). Vehicles that have turbocharged engines in the MY 2024 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. 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, NHTSA does 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.²³⁰ To model parts sharing, NHTSA also does 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. NHTSA does not believe manufacturers will increase the displacement of their engines to accommodate HCR technology adoption.²³¹ Separately, as seen in the MY 2024 analysis fleet, manufacturers generally use HCR engines in applications where the vehicle's power requirements fall significantly below the HP threshold. In fact, the average HP for the sales-weighted average of vehicles in the MY 2024 analysis fleet that use HCR Engine Path technologies is 182 HP, demonstrating that HCR engine use has indeed been limited to lower HP applications, and well below the 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.²³² For more detailed discussion on this, see Chapter 3.1.1.2.3.

Second, NHTSA excludes pickup trucks and vehicles that share engines with pickup trucks from receiving internal combustion (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. NHTSA excludes 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 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.²³³ NHTSA assumes 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 MY 2024 analysis fleet has done so. NHTSA excludes vehicles that share engines with pickup trucks from receiving IC-only HCR technology to model parts sharing decisions.

Finally, NHTSA restricts HCR engine application for some manufacturers that are heavily performance-focused and have demonstrated a significant commitment to power-dense technologies, such as

²³⁰ Heywood 2018, Chapter 5.

²³¹ 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 Automotive Trends Report, at pp. 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.

²³² See the Ford Maverick HEV. The reported total system for the Ford Maverick HEV is also 191 HP, well below the 405 HP threshold. See also the Lexus LC/LS 500h. The Lexus LC/LS 500h also uses premium fuel to reach this performance level.

²³³ 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 pickup 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.").

turbocharged downsizing.²³⁴ This means that no vehicle manufactured by these manufacturers can receive an HCR engine. Again, NHTSA implements 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 at least a 40V 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.²³⁵ VCR technology requires a complete redesign of the engine, and in the analysis fleet, only two of Nissan's models and one Infiniti model have incorporated this technology.

Few manufacturers and suppliers provided information about VCR technologies, and NHTSA 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, NHTSA limited adoption of the VCR engine technology to OEMs that have already employed the technology and their partners. NHTSA does 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

²³⁴ 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.

²³⁵ Nissan and Mitsubishi are strategic partners and members of the Renault-Nissan-Mitsubishi Alliance.

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 the light-duty analysis. Though the CAFE Model can apply diesel technology to basic engines, it is a rather costly and complex technology for a manufacturer to adopt. It is therefore unlikely that diesel technology will be applied to a non-diesel basic engine in the CAFE Model, which follows the observed trend that for more than a decade, diesel engine technologies have been used in less than 1 percent of the total light-duty fleet production in the United States.

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.

NHTSA simulates effectiveness values for engine technologies in two ways. NHTSA either calculates the value based on the difference in full-vehicle simulation results created using the Autonomie modeling tool, or NHTSA determines 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 10 light-duty vehicle technology classes, are shown in Figure 3-5. 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 3-14 for several specific examples. NHTSA shows the change in fuel consumption values between entire technology keys,²³⁶ and not the individual technology effectiveness values. Using the change between whole technology keys captures the complementary or non-complementary interactions among technologies.

Table 3-14: Example of Effectiveness Calculations Shown in Figure 3-5

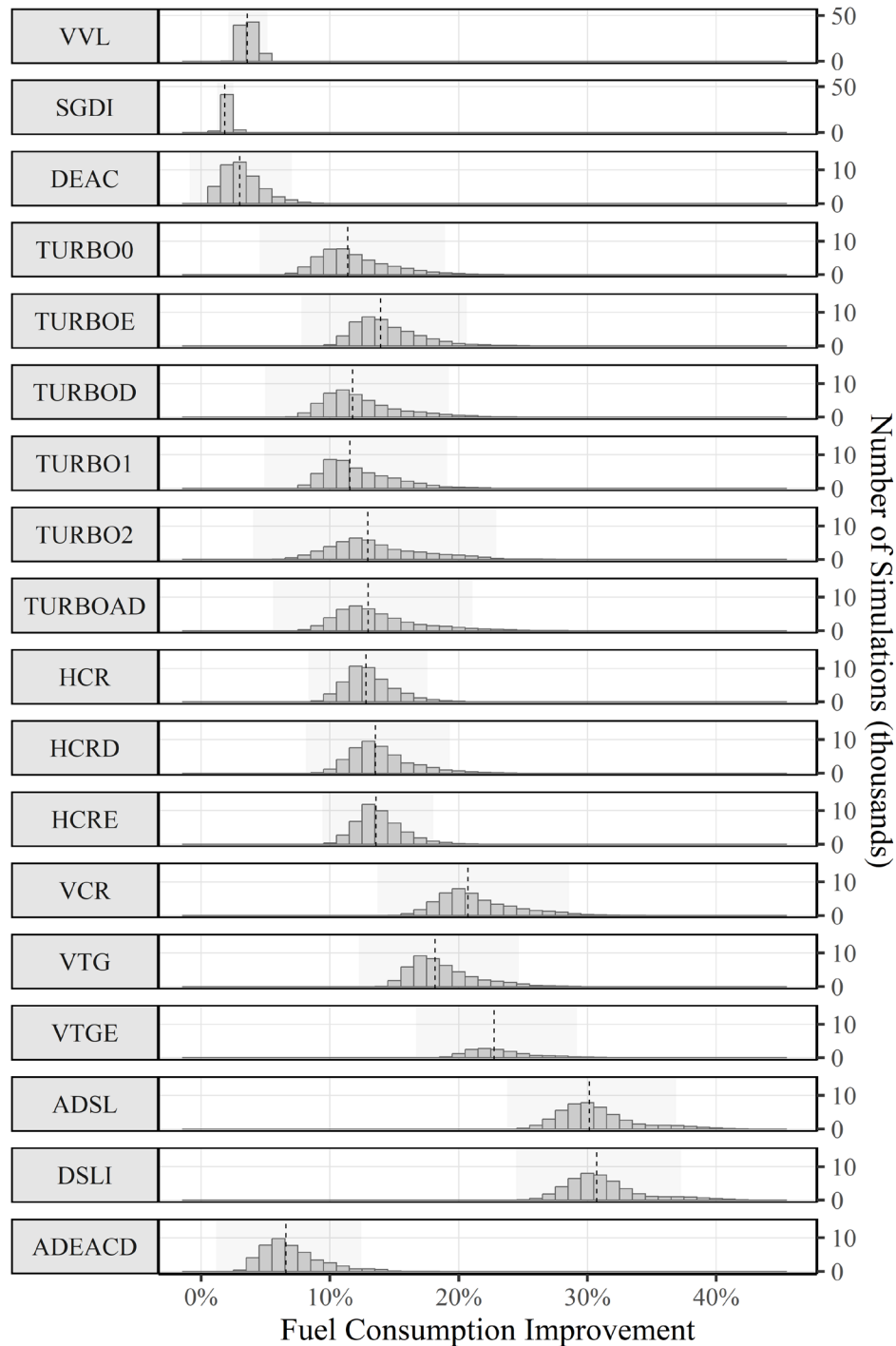
Tech	Vehicle Tech Class	Initial Technology Key	Fuel Consumption		Effectiveness (%)
			Initial (gal/mile)	New (gal/mile)	
TURBO1	Medium Non-Performance	DOHC;;;;;AT8L2;SS12V;ROLL10;AERO5;MR2	0.02835	0.02501	11.78
TURBO1	Medium Non-Performance	DOHC;;;;;AT8L2;CONV;ROLL10;AERO5;MR2	0.02927	0.02556	12.68
TURBO1	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

²³⁶ Technology key is combination of technologies that constitutes a specific vehicle, see Chapter 2.3.6.

*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.¹

The full data set NHTSA used to generate this example can be found in the CAFE Model Fuel Economy Adjustment Files.

Figure 3-5: Engine Technology Effectiveness Values for All LD Vehicle Technology Classes



The following subchapters discuss how NHTSA determined the effectiveness of the engine technologies on the simulated vehicle system’s performance in the rulemaking analysis. NHTSA first discusses the

values determined directly from the Autonomie simulations, followed by the values 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 NHTSA uses 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 on the vertical axis.²³⁷ A third engine characteristic, such as BSFC,²³⁸ 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. NHTSA refers to the engine maps developed to model the behavior of the engines in this analysis as engine map models.

The engine map models NHTSA uses in this analysis are representative of technologies currently in production or expected to be available in the rulemaking timeframe. NHTSA develops 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. NHTSA targets a broadly 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, NHTSA expects that the engine maps developed for this analysis will differ from engine maps for manufacturers' specific engines. However, NHTSA intends and expects that the incremental changes in performance modeled for this analysis, due to changes in technologies or technology combinations, will be like the incremental changes in performance observed in manufacturers' engines for the same changes in technologies or technology combinations.

Note that NHTSA never applies absolute BSFC levels from the engine maps to any vehicle model or configuration for the rulemaking analysis. NHTSA only uses the absolute fuel economy values from Autonomie full-vehicle 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 compliance data. For subsequent technology changes, NHTSA applies 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, NHTSA uses a small number of base level engine configurations with well-defined BSFC maps, and then, in a very systematic and controlled process, adds 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 NHTSA 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

²³⁷ BMEP is an engineering measure, independent of engine displacement, which indicates the actual work an engine performs.

²³⁸ BSFC is the rate of fuel consumption divided by the power being produced.

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. NHTSA 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 enable the agency to 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. In addition, 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.²³⁹

3.1.4.1.1. Engine Map Models

IAV GmbH (IAV) Engineering developed most of the engine map models NHTSA uses 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.²⁴⁰ 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 light-duty diesel engine maps for this analysis. SwRI has been providing automotive science, technology, and engineering services for over 70 years.²⁴¹ Much like the approach IAV has taken to develop light-duty engine maps, SwRI has followed a similar approach to developing the light-duty diesel 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 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.²⁴² 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 3-6, 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; and

²³⁹ See the following files, which can be found in the rulemaking docket by filtering for Supporting & Related Material: 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 - 220811.xlsx' ANL - Summary of Main Component Performance Assumptions - (2b-3) FY22 NHTSA - 220811.xlsx.

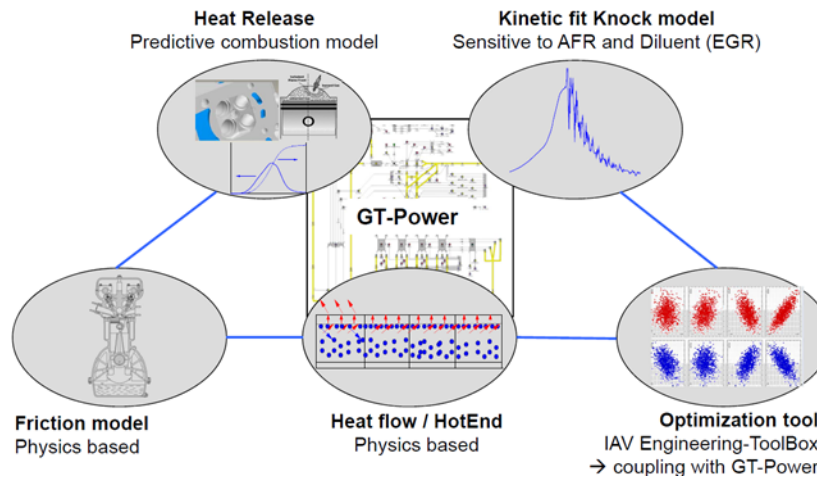
²⁴⁰ IAV Automotive Engineering, available at: <https://www.iav.com/> (accessed: May 25, 2026).

²⁴¹ Southwest Research Institute, available at: <https://www.swri.org> (accessed: May 25, 2026).

²⁴² For additional information on the GT-POWER tool, see <https://www.gtisoft.com/gt-power/> (accessed: May 25, 2026).

- IAV's proprietary Optimization Toolbox.²⁴³

Figure 3-6: Overview of the Engine Model and Sub-Models Used to Develop Engine Maps



IAV uses benchmark production engine test data, component test data, and manufacturer and supplier 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 reoptimizes 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 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 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 Chapter 3.1.1 Table 3-15 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.

²⁴³ 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.

- All gasoline engine optimization assumes the use of Tier 3 (E10 87 Anti-Knock Index (AKI))²⁴⁴ fuel to ensure the engines are capable of operating on regular gasoline (87 pump octane = $(R+M)/2$).^{245,246}
- 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, 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, and residual gas concentration.
- The combustion stability model is trained using Coefficient of Variation (COV) of Indicated Mean Effective Pressure (IMEP)^{247,248} 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.²⁴⁹ IAV and SwRI also validate the effectiveness values from the simulation results against detailed engine maps produced from the Argonne

²⁴⁴ Currently, throughout the United States, pump fuel is a blend of 90 percent gasoline and 10 percent ethanol.

²⁴⁵ 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, mid-grade typically 89-90 AKI, and premium 91-94 AKI. In higher altitude regions, the lowest octane fuel is typically 85 AKI.

²⁴⁶ EIA, Gasoline Explained, last revised: Nov. 17, 2022, available at: <https://www.eia.gov/energyexplained/gasoline/octane-in-depth.php> (accessed: May 25, 2026).

²⁴⁷ IMEP is the mean effective pressure calculated with indicated (theoretical) power of the engine.

²⁴⁸ Industry and researchers use a measurement known as coefficient of variation of IMEP (COV of IMEP) to evaluate combustion stability.

²⁴⁹ Friedrich, I. *et al.*, Automatic Model Calibration for Engine-Process Simulation With Heat-Release Prediction, SAE Technical Paper 2006-01-0655, Warrendale, PA: SAE International (2006), available at: <https://doi.org/10.4271/2006-01-0655> (accessed: May 25, 2026); Rezaei, R. *et al.*, Zero-Dimensional Modeling of Combustion and Heat Release Rate in DI Diesel Engines, *SAE International Journal of Engines*, Vol. 5(3): 874 – 85 (2012), available at: <https://doi.org/10.4271/2012-01-1065> (accessed: May 25, 2026); Berndt, R. *et al.*, Multistage Supercharging for Downsizing With Reduced Compression Ratio, *MTZ Worldwide*, Vol. 76: pp. 10 – 15 (2015), available at: <https://doi.org/10.1007/s38313-015-0036-4> (accessed: May 25, 2026); Neukirchner, H. *et al.*, Symbiosis of Energy Recovery and Downsizing, *MTZ Worldwide*, Vol. 75, pp. 4 – 9 (2014), available at: <https://doi.org/10.1007/s38313-014-0219-4> (accessed: May 25, 2026).

engine benchmarking programs, as well as published information from industry and academia, which ensures reasonable representation of simulated engine technologies.^{250,251}

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 analyses. For a full discussion on how Argonne integrates the engine map models into the Autonomie simulations, refer to the CAFE Analysis Autonomie Documentation.²⁵² The light-duty engine map models that NHTSA uses in this analysis and their specifications are shown in Table 3-15.

Table 3-15: 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

²⁵⁰ Bottcher, L., & Grigoriadis, P., ANL – BSFC map prediction Engines 22-26, Washington, D.C.: National Highway Traffic Safety Association (2019), available at: https://lindseyresearch.com/wp-content/uploads/2021/09/NHTSA-2021-0053-0002-20190430_ANL_Eng-22-26-Updated_Docket.pdf (accessed: May 25, 2026).

²⁵¹ Reinhart, T., Engine Efficiency Technology Study, Final Report, SwRI Project No. 03.26457, San Antonio, TX: Southwest Research Institute (2022), available at: https://downloads.regulations.gov/EPA-HQ-OAR-2022-0829-0230/attachment_17.pdf (accessed: May 25, 2026).

²⁵² Islam, E. S. *et al.*, Vehicle Simulation Process to Support the Analysis for MY 2027 and Beyond CAFE and MY 2030 and Beyond HDPUV FE Standards, Report No. DOT HS 813 431, Washington, D.C.: National Highway Traffic Safety Administration (2023), available at: https://static.nhtsa.gov/nhtsa/downloads/CAFE/2023-NPRM-LD-2b3-2027-2035/Argonne-Databases/Documentation/ANL%20Autonomie%20Model%20Documentation_2023%20NPRM.pdf (accessed: May 25, 2026).

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 CEGR, 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	DSL1 - 3.0L Diesel + DEAC	Cylinder deactivation added to eng45	SwRI

3.1.4.2. Alternative Modeled Values – Analogous Effectiveness Values

For most engine technologies considered in the analysis, NHTSA derives the fuel economy improvements from the database of Autonomie full-vehicle simulation results. However, the analysis also incorporates a handful of what NHTSA refers to as “analogous effectiveness values.” NHTSA determines 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, NHTSA conducts a pairwise comparison between technology configurations that included the DOHC engine (Eng1) and the DOHC +SGDI (Eng18) engine. Then, NHTSA uses 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.

NHTSA performs 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 relative 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 3-16 shows the engine technologies where analogous effectiveness values are used.

Table 3-16: LD 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. NHTSA sponsored research to determine DMCs for fuel-saving technologies.²⁵³ NHTSA then applies 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 2024 dollars, can be found in the Technologies Input File. NHTSA discusses the application of RPE and cost learning to the DMCs in Chapter 2.

NHTSA uses absolute costs in this analysis instead of relative costs, which were used prior to the 2020 CAFE rulemaking. NHTSA uses absolute costs to ensure the full cost of the ICE is removed when the Model applies hybrid technologies. Relative costs can still be determined through comparison of the absolute costs for the initial technology combination and the new technology combination.

The costs NHTSA uses to model the application of engine technologies can be found across multiple tabs of the Technologies Input File. NHTSA determines engine costs based on engine size and configuration, instead of vehicle technology class. NHTSA designates the engine cost tabs in the Technologies Input File based on the 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) engine designations are for engines with a SOHC

²⁵³ 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 Institute for teardown studies evaluating mass reduction 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.

architecture or OHV architectures respectively. However, for costing purposes, NHTSA assumes all engines are DOHC once advanced engine technologies are applied. NHTSA determines cylinder count, engine architecture, and configuration by assignment in the Market Data Input File, see Chapter 3.1.2. Table 3-17 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 3-17: 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.²⁵⁴ 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 3-18 provides a small example set of the costing configurations for turbo downsized technologies versus the base engine configuration costing tab.

Table 3-18: Examples of How LD 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.	

²⁵⁴ Heywood 2018, Chapter 6.2.8.

NHTSA allows additional downsizing beyond what has been previously modeled because manufacturers have downsized low output, naturally aspirated engines to small architecture turbo engines.^{255,256,257} NHTSA identifies 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 3-19 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.

²⁵⁵ Truett, R. GM Bringing 3-Cylinder back to North America, last revised: Dec. 1, 2019, available at: <https://www.autonews.com/cars-concepts/gm-bringing-3-cylinder-back-na> (accessed: May 25, 2026).

²⁵⁶ Stoklosa, A., Tested: Mini Cooper Hardtop, last revised: Dec. 2, 2014, available at: <https://www.caranddriver.com/reviews/a15109143/2014-mini-cooper-hardtop-manual-test-review> (accessed: May 25, 2026).

²⁵⁷ Leanse, A., 2020 Ford Escape Options: Hybrid vs. 3-Cylinder EcoBoost vs. 4-Cylinder EcoBoost, last revised: Sept. 24, 2019, available at: <https://www.motortrend.com/news/2020-ford-escape-engine-options-pros-and-cons-comparison> (accessed: May 25, 2026).

Table 3-19: 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 3-20: 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)	DSL1 (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 3-21. NHTSA sourced these costs from publications and historical cost studies^{258,259} and updated them to 2024 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 NHTSA does not use unit DMC costs but applies an incremental DMC for the various cylinder count configurations.

Table 3-21: Examples of Basic Engine Technology Incremental DMCs Used for the LD Analysis in 2024 Dollars

Engine Technologies – Direct Manufacturer Costs (2024\$) for Basic Engine Technologies								Incremental To
Tech	Basis	Unit DMC	DMC for	DMC for	DMC for	DMC for	DMC for	
			4-Cylinder	4-Cylinder	6-Cylinder	6-Cylinder	8-Cylinder	
			1-Bank	2-Bank	1-Bank	2-Bank	2-Bank	
VVL	Cylinder	68	273	273	410	410	546	Base Engine
SGDI	Cylinder	76	302	302	453	453	604	Base Engine
DEAC	-	-	140	140	166	166	187	Base Engine
ADEACS	Cylinder	59	235	235	353	353	470	SGDI, DEAC
ADEAC D	Cylinder	110	439	439	658	658	877	SGDI, DEAC

NHTSA applies RPE and learning factors to the incremental DMCs (see Chapter 2.6). To reach an absolute cost starting point, NHTSA sums 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 Technologies Input Files. For the basic engines, to calculate an absolute cost, NHTSA assigns a base engine cost to the engine (examples are shown in Table 3-22), then adds an incremental cost for each basic engine technology (examples are shown in Table 3-23). As an example, a 4C1B DOHC engine with VVL and SGDI has an absolute cost of \$7,305.77 (6,522.78+371.80+411.19) for MY 2024 in 2024 dollars. Table 3-24 shows examples of absolute costs for ADEACS and ADEACD engines.

Table 3-22: Examples of Base Absolute Costs for MY 2024 LD Basic Engine Technologies in 2024 Dollars

	4C1B	6C2B	8C2B
SOHC	6,229	7,139	7,910
DOHC	6,523	7,727	8,498
OHV	NA	7,238	8,009

²⁵⁸ Kolwich, G., Diesel Cost Analysis, FEV, P311732-02, Rochester Hills, MI: FEV North America, Inc., p. 259 (2015), available at: https://downloads.regulations.gov/NHTSA-2023-0022-0017/attachment_55.pdf (accessed: May 25, 2026).

²⁵⁹ 2015 NAS report, at p. 7.

Table 3-23: Examples of Incremental Absolute Costs for Adding LD Basic Engine Technologies for MY 2024 in 2024 Dollars

	4C1B	6C2B	8C2B
VVL	372	558	744
SGDI	411	617	822
DEAC	190	224	253

Table 3-24: Examples of Absolute Costs for ADEACS and ADEACD Technologies for MY 2024 in 2024 Dollars

	4C1B	6C2B	8C2B
ADEACS	7,478	9,098	10,280
ADEACD	7,784	9,558	10,893

*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

NHTSA determines 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

NHTSA calculates 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 3-25.

NHTSA continues the same methodology for the TURBOE, TURBOD, TURBO1, TURBO2, and TURBOAD technology costs in the same manner as TURBO0. For TURBOE NHTSA adds the respective incremental costs of CEGR to the TURBO0 technology cost. For TURBOD NHTSA adds the respective incremental costs of DEAC to the TURBO0 technology. For TURBO1 NHTSA adds the respective incremental costs to TURBO0. For TURBO2 NHTSA adds the respective incremental costs to TURBO1, and for TURBOAD NHTSA adds the respective incremental costs of ADEACD to TURBO0. NHTSA applies the rules for cost downsizing discussed above, for each forced induction engine technology.

Table 3-25 below shows the DMCs for forced induction engines in the light-duty analysis, in 2024 dollars. The TURBOAD technology also includes an incremental cost of \$140 for 4-cylinder, \$166 for 6-cylinder, and \$187 for 8-cylinder engines that is added to the unit DMC cost. Table 3-26 shows examples of absolute costs for the LD 4C1B turbo engines,²⁶⁰ across multiple model years, demonstrating the application of both the RPE and learning rates. Table 3-27 also shows examples of 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 Technologies Input Files.

²⁶⁰ These costs represent the cost for a 6C2B naturally aspirated engine to become a forced induction (turbo) engine, per examples discussed in Table 3-27.

Table 3-25: Examples of LD Turbocharged Downsized Engine Incremental DMCs in 2024 Dollars

Engine Technologies – Direct Manufacturer Costs (2024\$) for Turbocharged Technologies				Incremental To				
Tech	Basis	Unit DMC	DMC for	DMC for	DMC for	DMC for	DMC for	
			4-Cylinder	4-Cylinder	6-Cylinder	6-Cylinder	8-Cylinder	
			1-Bank Engine	2-Bank Engine	1-Bank Engine	2-Bank Engine	2-Bank Engine	
TURBOE	None	-	353	353	353	353	353	TURBO0
TURBO1	Cyl	68	273	1,070	1,077	1,077	1,765	TURBO0
TURBO0	None	-	794	794	666	666	1,216	Base Engine
TURBOD	None		140	140	166	166	187	TURBO0
TURBO2	None	-	294	295	295	295	497	TURBO1
TURBOA D	Cyl	110	578	578	823	823	1,063	TURBO0

Table 3-26: Examples of LD Absolute Costs Used for I4 Turbocharged Engines in 2024 Dollars (costs include DMCs, RPE, and learning rate factor)

	4C1B Costs (2024\$)			
Technology	2020	2022	2026	2030
TURBO0	7,452	7,432	7,406	7,388
TURBOE	7,958	7,917	7,856	7,815
TURBOD	7,647	7,624	7,594	7,573
TURBO1	7,833	7,808	7,774	7,749
TURBO2	8,539	8,457	8,314	8,220
TURBOAD	8,173	8,117	8,047	8,002

Table 3-27: Examples of LD Absolute Costs Used for V6 Turbocharged Engines in 2024 Dollars (costs include DMC, RPE, and learning rate factor)

	6C2B Costs (2024\$)			
Technology	2020	2022	2026	2030
TURBO0	8,506	8,488	8,467	8,452
TURBOE	9,012	8,974	8,917	8,879
TURBOD	8,736	8,716	8,689	8,670
TURBO1	9,078	9,053	9,019	8,993
TURBO2	9,783	9,703	9,559	9,464
TURBOAD	9,587	9,516	9,429	9,373

3.1.5.2.2. High Compression Ratio Engines

NHTSA uses DMCs for HCR engines based on the 2015 NAS analysis, but the cost accounting is aggregated differently than the 2015 NAS report. NHTSA includes other technologies present in the engines, like SGDI, and the configuration of the engine, such as SOHC versus DOHC in the cost estimates. Finally, NHTSA determines the high compression ratio engine with cooled exhaust gas recirculation (HCRE) and high compression ratio engine with cylinder deactivation (HCRD) technology cost by adding the CEGR and DEAC costs, respectively, to the HCR engine costs. Examples of the HCR DMC values are shown in Table 3-28.

NHTSA then applies an RPE factor and learning curve. Table 3-29 and Table 3-30 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 3-28: Examples of HCR Technology Incremental DMCs in 2024 Dollars

Engine Technologies – Direct Manufacturer Costs (2024\$) for HCR Technologies								Incremental To
Tech	Basis	Unit DMC	DMC for	DMC for	DMC for	DMC for	DMC for	
			4-Cylinder	4-Cylinder	6-Cylinder	6-Cylinder	8-Cylinder	
			1-Bank Engine	2-Bank Engine	1-Bank Engine	2-Bank Engine	2-Bank Engine	
HCR	none	-	520	520	520	520	520	Base Engine
HCRE	none	-	353	353	353	353	353	HCR
HCRD	none	-	140	144	166	166	187	HCR

Table 3-29: Examples of Absolute Costs for I4 HCR Engines (costs include DMC, RPE, and learning rate factor) in 2024 Dollars

	4C1B Costs (2024\$)			
Technology	2020	2022	2026	2030
HCR	6,796	6,749	6,700	6,677
HCRE	7,302	7,235	7,150	7,103
HCRD	6,991	6,942	6,888	6,861

Table 3-30: Examples of Absolute Costs for V6 HCR Engines (costs include DMC, RPE, and learning rate factor) in 2024 Dollars

	6C2B Costs (2024\$)			
Technology	2020	2022	2026	2030
HCR	8,000	7,953	7,904	7,881
HCRE	8,506	8,439	8,354	8,307
HCRD	8,230	8,180	8,126	8,098

3.1.5.2.3. Miller Engines

NHTSA uses cost data from an FEV technology cost assessment, performed for ICCT, to estimate the DMC for Miller cycle engines with VTG.²⁶¹ NHTSA considered costs from the 2015 NAS study that referenced a NESCCAF 2004 report,²⁶² 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, NHTSA 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. NHTSA uses 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, NHTSA built a cost for electrically assisted variable supercharger VTGE (Eng23c) engines based on the 2015 NAS report that uses a cost of \$1,050 (2010\$) plus the cost of the mild hybrid battery. Examples of the DMC for these technologies are shown in Table 3-31. Example costs are shown in Table 3-32 for 4C1B engines and Table 3-33 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 3-31: Examples of Incremental DMCs Used for Miller Cycle Engines (VTG, VTGE) in 2024 Dollars

Engine Technologies – Direct Manufacturer Costs (2024\$) for Miller Technologies					Incremental To
Tech	DMC for	DMC for	DMC for	DMC for	
	4-Cylinder	6-Cylinder	6-Cylinder	8-Cylinder	
	1-Bank Engine	1-Bank Engine	2-Bank Engine	2-Bank Engine	
VTG	755	755	755	755	TURBO2
VTGE	1,473	1,473	1,473	1,473	VTG

Table 3-32: Examples of Miller Cycle I4 Engines' Absolute Costs Used for VTG and VTGE Technology (costs include DMC, RPE, and learning rate factor) in 2024 Dollars

Technology	4C1B Costs (2024\$)			
	2020	2022	2026	2030
VTG	9,620	9,495	9,276	9,132
VTGE	11,553	11,223	10,737	10,405

²⁶¹ Isenstadt A. *et al.*, Downsized, Boosted Gasoline Engines, Draft, International Council on Clean Transportation (2016), available at: <https://theicct.org/publication/downsized-boosted-gasoline-engines-2/> (accessed: May 25, 2026).

²⁶² NESCCAF, Reducing Greenhouse Gas Emissions from Light-Duty Motor Vehicles, Boston, MA: NESCCAF (2004), available at: <https://www.nesccaf.org/activities/reports> (accessed: May 25, 2026).

Table 3-33: Examples of Miller Cycle V6 Engines’ Absolute Costs Used for VTG and VTGE Technologies (costs include DMC, RPE, and learning rate factor) in 2024 Dollars

	6C2B Costs (2024\$)			
Technology	2020	2022	2026	2030
VTG	10,865	10,740	10,521	10,377
VTGE	12,797	12,468	11,982	11,649

3.1.5.2.4. Variable Compression Ratio Engines

The base DMCs that NHTSA uses for VCR engines are based on data from the 2015 NAS report.²⁶³ The 2015 NAS cost for VCR in MY 2025 uses a naturally aspirated engine; however, for this analysis NHTSA adds the cost of CEGR. Table 3-34 shows an example estimated DMC for the VCR technology. Examples of the absolute costs for 4C1B and 6C2B engines, respectively, are in Table 3-35 and Table 3-36.

Table 3-34: Examples of VCR DMCs in 2024 Dollars

Engine Technologies – Direct Manufacturer Costs (2024\$)						Incremental To
Tech	Basis	Unit DMC	DMC for	DMC for	DMC for	
			4-Cylinder	6-Cylinder	8-Cylinder	
			1-Bank Engine	2-Bank Engine	2-Bank Engine	
VCR	cylinder	210	839	1,258	1,677	TURBO1

Table 3-35: Examples of Absolute VCR Engine Costs for I4 Engine Configuration (costs include DMC, RPE, and learning rate factor) in 2024 Dollars

	4C1B Costs (2024\$)			
Technology	2020	2022	2026	2030
VCR	9,229	9,134	9,015	8,937

Table 3-36: Examples of Absolute VCR Engine Costs for V6 Engine Configuration (costs include DMC, RPE, and learning rate factor) in 2024 Dollars

	6C2B Costs (2024\$)			
Technology	2020	2022	2026	2030
VCR	11,170	11,043	10,880	10,776

3.1.5.2.5. Diesel Engines

Diesel engine DMCs are based on the initial engine cost. The ADSL cost is based on the cost of a modern light-duty diesel engine.²⁶⁴ This technology includes a combination of low pressure and high

²⁶³ 2015 NAS report, at p. 7.

²⁶⁴ 2015 NAS report, at pp. 104 – 5.

pressure EGR, reduced parasitic loss, advanced friction reduction, a highly integrated exhaust catalyst with low temperature light-off, and closed loop combustion control. The second level of diesel technology (DSLI) includes the cost of incorporating cylinder deactivation to the base level diesel engine. In both ADSL and DSLI, the cost includes after-treatment systems to meet the emissions standards for criteria pollutants.²⁶⁵ See Chapter 3.1.1.2.6 for more discussion on the light-duty diesel technology.

Example costs for the light-duty diesel technologies are shown in Table 3-37, Table 3-38, and Table 3-39. All ADSL costs are shown in the LD Technologies Input Files.

Table 3-37: Examples of Incremental DMCs Used for LD Diesel Engines (ADSL, DSLI) in 2024 Dollars

Engine Technologies – Direct Manufacturer Costs (2024\$) for Diesel Technologies					Incremental To
Tech	DMC for	DMC for	DMC for	DMC for	
	4-Cylinder	6-Cylinder	6-Cylinder	8-Cylinder	
	1-Bank Engine	1-Bank Engine	2-Bank Engine	2-Bank Engine	
ADSL	4,334	4,334	4,334	4,334	Base Engine
DSLI	140	166	166	187	ADSL

Table 3-38: Examples of Absolute Diesel Engine Costs for LD I4 Engine Configuration (costs include DMC, RPE, and learning rate factor) in 2024 Dollars

Technology	4C1B Costs (2024\$)			
	2020	2022	2026	2030
ADSL	12,051	11,857	11,703	11,613
DSLI	12,234	12,034	11,875	11,782

Table 3-39: Examples of Absolute Diesel Engine Costs for LD I6 Engine Configuration (costs include DMC, RPE, and learning rate factor) in 2024 Dollars

Technology	6C1B Costs (2024\$)			
	2020	2022	2026	2030
ADSL	12,634	12,441	12,287	12,197
DSLI	12,850	12,649	12,489	12,396

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, NHTSA classifies all light-duty vehicle transmissions into discrete transmission technology paths. NHTSA uses the paths to model the most representative characteristics, costs, and

²⁶⁵ 2015 NAS report, at p. 104.

performance of the fuel-economy-improving transmissions most likely available during the rulemaking timeframe.

The following subchapters discuss how NHTSA defines transmissions in the light-duty fleet. 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 NHTSA assigns transmission technology and transmission adoption features to the light-duty fleet.

3.2.1. Transmission Technologies

In this analysis, NHTSA only models automatic transmissions (AT). ATs are characterized by automatically selecting and shifting between transmission gears for the driver during vehicle operation. NHTSA subdivided light-duty ATs into four subcategories: traditional ATs, dual-clutch transmissions (DCT), and CVT and electronic continuously variable transmissions (eCVT). 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 percent of the vehicles produced in MY 2021.²⁶⁶ Due to the trending decline of manual transmissions and their current low production volumes, NHTSA has removed manual transmissions from this analysis. All MY 2024 vehicles with manual transmissions are mapped as DCTs and assume the DCT costs in the MY 2024 fleet for the LD analysis.

eCVTs are also not discussed in detail in this analysis and are not specifically shown in the technology pathways.²⁶⁷ 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.²⁶⁸ eCVTs are considered integral parts of hybrid drivetrains (such as power-split hybrids) and are not applied as a standalone technology. See Chapter 3.2.2 for a discussion of how NHTSA assigns the eCVT in the analysis fleet.

NHTSA also includes the application of HEG technology improvements as options to transmissions (designated as L2 or L3 in the 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. NHTSA considers three levels of HEG improvements in this analysis based on NAS 2015 recommendations and CBI data.²⁶⁹ NHTSA applies 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 7-speed automatic transmissions (AT7), 9-speed automatic transmissions (AT9), and 10-speed automatic transmissions (AT10) during the same 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. NHTSA identifies transmissions for the light-duty analysis by technology type, gear count, and HEG technology level using the naming conventions shown in Table 3-40 below.

²⁶⁶ 2024 EPA Automotive Trends Report.

²⁶⁷ Used in accordance with 49 U.S.C. 329029(h) constraints.

²⁶⁸ FEV, Inc., Light Duty Technology Cost Analysis, Power-Split and P2 HEV Case Studies, Technical Report, EPA-420-R-11-015, Washington, DC: EPA, available at: <https://nepis.epa.gov/Exe/ZyPDF.cgi/P100EG1R.PDF?Dockey=P100EG1R.PDF> (accessed: May 26, 2026).

²⁶⁹ 2015 NAS Report, at p. 191.

Table 3-40: 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.²⁷⁰ 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. NHTSA includes ATs with gear counts ranging from 5 speeds to 10 speeds in the light-duty analysis, see Figure 3-8.²⁷¹

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 connect the engine and transmission directly (“lockup”).

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, NHTSA and EPA surveyed ATs in the market to assess trends in gear count and purported fuel economy improvements.²⁷² Based on that survey, and EPA’s more recent Automotive Trends Reports,²⁷³ NHTSA models ATs with a range of 5 to 10 gears with 3 levels of HEG technology.

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

²⁷⁰ 2024 EPA Automotive Trends Report.

²⁷¹ Specifically, NHTSA considered 5-speed automatic transmissions (AT5), 6-speed automatic transmissions (AT6), 7-speed automatic transmission (AT7), 8-speed automatic transmissions (AT8), 9-speed automatic transmissions (AT9), and 10-speed automatic transmissions (AT10).

²⁷² EPA, Regulatory Impact Analyses for Air Pollution Regulations, Last updated: July 1, 2025, available at: <https://www.epa.gov/economic-and-cost-analysis-air-pollution-regulations/regulatory-impact-analyses-air-pollution> (accessed: May 26, 2026).

²⁷³ 2024 EPA Automotive Trends Report.

speed ratio between the pulleys. This ratio change is smooth and continuous, unlike the step changes of other transmission varieties.²⁷⁴

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,^{275,276} and approaches the CVT’s ability to operate the engine at the most efficient operating point. Though 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.²⁷⁷ 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.²⁷⁸ Due to the current limited torque capacity of CVTs, this technology does not appear in high torque or high load applications in the light-duty fleets.

NHTSA models two types of CVT systems in the light-duty analysis, the basic level CVT and a CVT with HEG technology applied, see Figure 3-8. As discussed above, eCVTs are not modeled as a standalone technology but are incorporated in power-split hybrids (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.²⁷⁹ DCTs have encountered issues with customer acceptance.²⁸⁰ The NAS also stated in its 2021 report that “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 converter-based automatic transmission performance seem to have

²⁷⁴ 2015 NAS report, at p. 171.

²⁷⁵ Robinette, D., & Wehrwein, D., 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: May 25, 2026).

²⁷⁶ Greimel, H., ZF CEO: We’re Not Chasing 10-Speeds, Automotive News, last revised: Nov. 23, 2014, available at: <https://www.autonews.com/article/20141123/OEM10/311249990/zf-ceo-we-re-not-chasing-10-speeds/> (accessed: May 25, 2026).

²⁷⁷ 2015 NAS report, at p. 183.

²⁷⁸ 2015 NAS report, at p. 264.

²⁷⁹ 2024 EPA Automotive Trends Report, at p. 78.

²⁸⁰ See 2015 NAS report, at pp. 170 – 1.

concerns with a start-up clutch, mostly at lower speeds. Therefore, some automakers have since transitioned away from DCT, and other automakers scrapped introduction plans prior to launch.”²⁸¹

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, NHTSA constrains application of additional DCT technology to vehicles already using DCT technology, and only models two types of DCTs in the analysis, see Figure 3-8.

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 U.S. vehicle market for MY 2024. 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 3-41 lists the Autonomie transmission models and their acronyms that NHTSA uses in the CAFE Model Input File for the light-duty analysis. For convenience, NHTSA refers to these technologies by their acronyms in this subchapter.

NHTSA classifies the wide variety of transmissions in the light-duty market into discrete transmission technology paths. NHTSA uses 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 transmission technology likely to be available during the rulemaking timeframe.

To assess the feasibility of different stringencies, it is important to establish the initial technology content of the fleet. Underestimating the amount of technology in the analysis fleet could lead to overestimating the actual technology application needed for manufacturers to comply with standards and cause the analysis to apply technologies incorrectly 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.

Manufacturer mid-model year CAFE compliance submissions and publicly available manufacturer specification sheets serve as the basis for initial transmission assignments. NHTSA uses these data to assign transmissions in the analysis fleet and determine which platforms share transmissions. Common transmissions and how NHTSA characterizes them are discussed in Chapter 3.2.3.

Table 3-41: LD Transmission Technologies

Transmission	Name
5-speed automatic	AT5
6-speed automatic	AT6

²⁸¹ 2021 NAS report.

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

NHTSA specifies transmission type, number of gears, and high-efficiency gearbox (HEG) level for the light-duty initial fleet assignments. Transmission types in the light-duty analysis include automatics, direct drive, dual-clutch, and continuously variable, as described in Chapter 3.2.1. HEG levels represent incremental improvements in transmission technology that improve efficiency for automatic and CVT. 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 (NHTSA assigns DCTs with seven and nine gears to DCT6 and DCT8, respectively). As discussed above, NHTSA does not model manual transmissions in Autonomie due to their rarity. NHTSA assigns any initial fleet vehicles with a 5- or 6-speed manual transmission as DCT6 and assigns 7-speed manual transmissions as DCT8.

For ATs and CVTs, identifying the most appropriate transmission path model requires additional steps because identifying the HEG level from specification sheets alone is not always straightforward. NHTSA reviews 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 the MY 2024 light-duty initial analysis fleet. However, for the LD analysis, NHTSA found all 7-speed, 9-speed, 10-speed, and some 8-speed AT to be advanced transmissions operating at HEG Level 2 equivalence (see Chapter 3.2.1). Eight-speed ATs and CVTs were introduced in MY 2016 and are assigned to HEG Level 2 for the light-duty fleet. All other transmissions are assigned to their respective transmission’s initial level. HEG level 1 technologies available include AT6, AT8, and CVT.

NHTSA assigns any vehicle in the light-duty analysis fleet with a SHEVPS powertrain as 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 hybrid vehicles, see Chapter 3.2.1.

Table 3-42 shows the prevalence of each transmission technology as assigned in the light-duty analysis fleets.

Table 3-42: Penetration Rates of Transmission Technologies in the MY 2024 LD Analysis Fleet²⁸²

Transmission Technology	Sales Volume	Penetration Rate
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²⁸² These estimated penetrate rates are based on the 2024 Reference Fleet that is used for the standard-setting or constrained analysis.

cAT5	100,830	0.74%
AT6	825,990	6.03%
AT7L2	29,259	0.21%
AT8	3,117,283	22.74%
AT8L2	1,410,983	10.29%
AT8L3	-	0%
AT9L2	976,037	7.12%
AT10L2	1,926,667	14.06%
AT10L3	-	0%
DCT6	343,672	2.51%
DCT8	167,639	1.22%
CVT	1,465,839	10.69%
CVTL2	1,525,480	11.13%
eCVT (Total HEV and PHEV)	1,816,541	13.25%
Total AT	8,387,049	61.19%
Total DCT	511,311	3.73%
Total CVT	2,991,319	21.82%

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, NHTSA considers 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, NHTSA characterizes transmissions in the analysis fleet by drive type and vehicle architecture. NHTSA considers front-, rear-, all-, and 4-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, production locations, or both, show that manufacturers use transmissions that are the same or similar on multiple vehicle models. Manufacturers have told the agency 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 analysis fleet with the same transmission configuration adopt additional fuel-saving transmission technology together, as described in Chapter 2.2.1.6.

NHTSA assigns 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. NHTSA distinguishes 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 transmission technology independently.

Note that when determining the drive type of a transmission, the assignment of AWD versus 4-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 fleet 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 4 wheels and a longitudinal engine (RWD architecture) are assigned 4-wheel drive. An example of where NHTSA 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 4-wheel drive.

3.2.3. Transmission Adoption Features

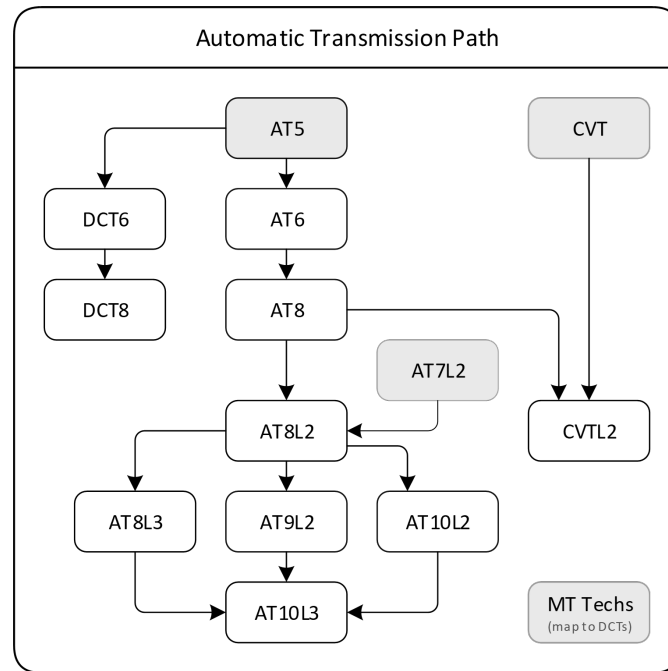
When evaluating transmission technologies to improve fuel economy, the CAFE Model considers current transmission architecture. If a manufacturer has already committed to advanced automatic, continuously variable, or DCTs on a vehicle, the CAFE Model will consider higher tier fuel-saving technologies along the current path. Transmission level technology pathways for the light-duty analysis are illustrated in Figure 3-7 below.²⁸³ The greyed AT5, AT7L2, and CVT nodes are only used as a starting point when NHTSA initially assigns the technologies to establish the light-duty analysis fleet.

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 DCT. 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).²⁸⁴ In addition, 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.

²⁸³ Technologies that can only be assigned in the baseline fleet include AT5, AT7L2, and CVT; they are shown as the grey boxes.

²⁸⁴ NHTSA, 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: May 25, 2026).

Figure 3-7: LD Transmission-Level Technology Pathways



Note that when hybrid 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 or plug-in hybrid 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 this, the AT path precludes adoption of other transmission types once a platform progresses past an AT8. NHTSA uses this restriction to avoid the significant level of stranded capital 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.²⁸⁵

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.

3.2.3.2. Continuously Variable Transmissions

CVT adoption is limited by technology path logic in the LD fleet analysis. Vehicles that do not originate with a CVT or vehicles with multi-speed transmissions beyond AT8 in the MY 2024 analysis fleet cannot adopt CVTs. Vehicles with multi-speed 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

²⁸⁵ 2024 EPA Automotive Trends Report, at p. 79, Figure 4.24.

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 LDVs 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. NHTSA believes the 300 lb.-ft restriction represents an increase over current levels of torque capacity that is likely to be achieved during the rulemaking 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.²⁸⁶ In addition, 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 consistent with manufacturers' technology choices.²⁸⁷

3.2.4. Transmission Effectiveness

NHTSA uses 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 transmission technologies and separates those contributions from other technologies in the full-vehicle system. The modeling approach follows the recommendations of the NAS in its 2015 LDV fuel economy technology report to use full-vehicle modeling, supported by application of collected improvements, at the sub-model level.²⁸⁸

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 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.²⁸⁹

NHTSA populates transmission template models in Autonomie with characteristics data to model specific transmissions.²⁹⁰ 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-

²⁸⁶ Market Data Input File.

²⁸⁷ 2024 EPA Automotive Trends Report, at p. 79, Figure 4.24.

²⁸⁸ 2015 NAS report, at p. 292.

²⁸⁹ Chapter titled "Autonomie" and Chapter "Vehicle and Component Assumption" of the CAFE Analysis Autonomie Documentation.

²⁹⁰ See the following files that can be found in the rulemaking docket by filtering for Supporting & Related Material: 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 - 220811.xlsx; ANL - Summary of Main Component Performance Assumptions - (2b-3) FY22 NHTSA - 220811.xlsx.

reviewed sources, transmission and vehicle testing programs, results from simulating current and future transmission configurations, and confidential data obtained from OEMs and suppliers.²⁹¹

For example, the 10-speed automatic transmission (AT10L2) efficiency curve uses data from SwRI for the 2017 Ford F-150 10R80 transmission.^{292,293} 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.²⁹⁴ Because this transmission is used in both cars and trucks, the SwRI data for this transmission are applicable to multiple vehicle classes.

NHTSA models 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.²⁹⁵ The AT8L2 has the same gear ratios as the AT8; however, NHTSA improves 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.

NHTSA comprehensively simulates 15 transmission technologies for the LD 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 LDV technology classes are shown in Figure 3-8. 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, for example, AT10L3, represents the addition of the AT10L3 technology to every technology combination that could add AT10L3. NHTSA emphasizes that the graph shows the change in fuel consumption values between entire technology keys,²⁹⁶ 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 and eCVT technologies is not shown. The eCVT transmissions do not have a standalone effectiveness because those technologies are only implemented as part of hybrid powertrains. The AT5 has no effectiveness values because it is a basic level technology against which all other transmission technologies are compared.

²⁹¹ Argonne National Laboratory, Downloadable Dynamometer Database, last revised: 2023, available at: <https://www.anl.gov/taps/downloadable-dynamometer-database> (accessed: May 25, 2026); Kim, N. *et al.*, Advanced Automatic Transmission Model Validation Using Dynamometer Test Data, SAE 2014-01-1778, Detroit, MI: SAE World Congress (2014), available at: <https://doi.org/10.4271/2014-01-1778> (accessed: May 25, 2026); Kim, N. *et al.*, 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 (2014), available at: <https://doi.org/10.1007/s12239-014-0027-5> (accessed: May 26, 2026).

²⁹² Chapter titled “Transmission Assumptions” of the CAFE Analysis Autonomie Documentation.

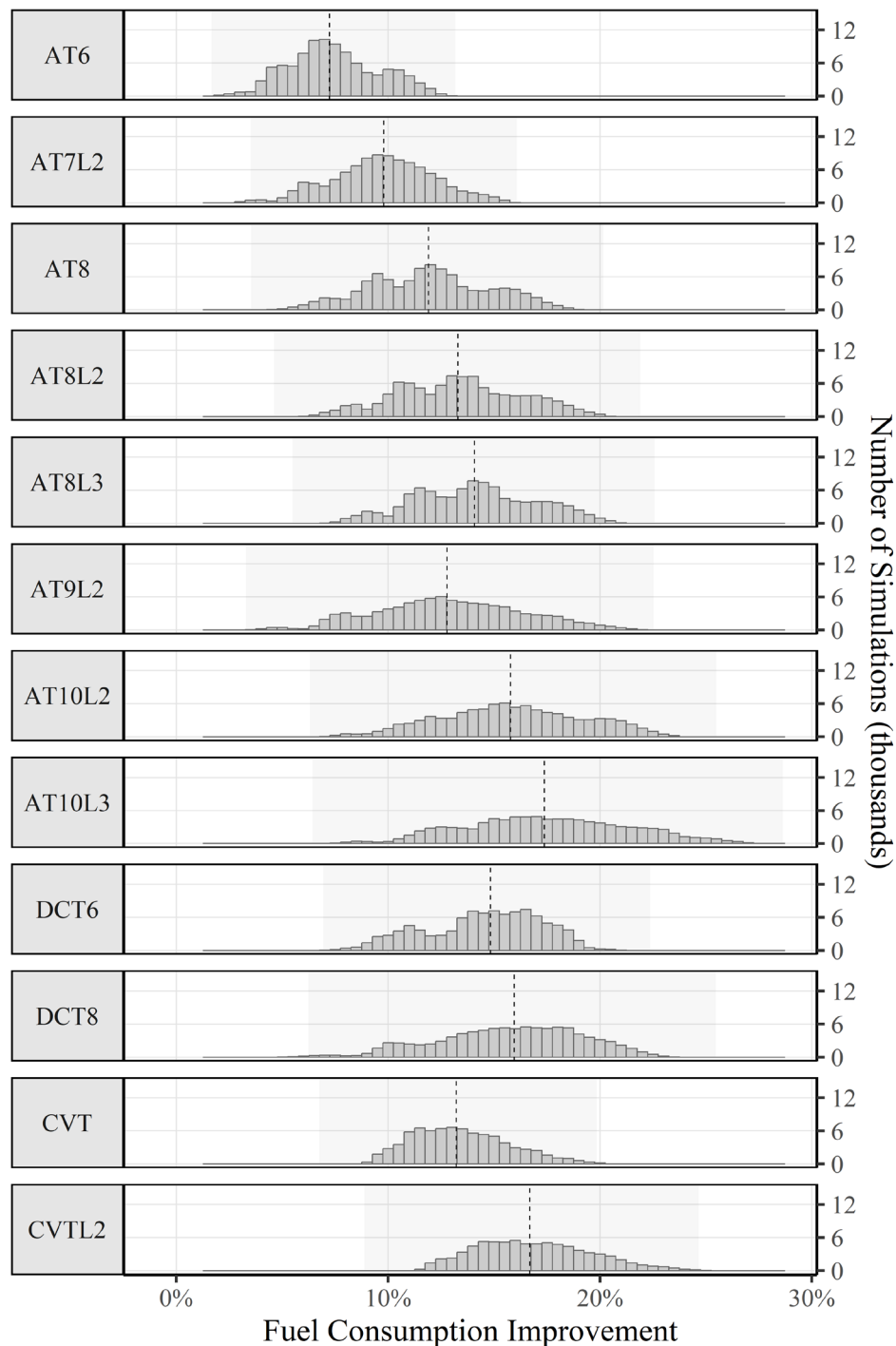
²⁹³ Wileman, C., Light-Duty Vehicle Transmission Benchmarking, 2017 Ford F-150 With 10R80 and 2018 Honda Accord With Earth Dreams CVT, Report No. DOT HS 813 163, Washington, D.C.: NHTSA (2021), available at: https://downloads.regulations.gov/NHTSA-2023-0022-0017/attachment_101.pdf (accessed: May 25, 2026).

²⁹⁴ Gears Magazine, 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: May 25, 2026).

²⁹⁵ CAFE Analysis Autonomie Documentation, Chapter titled “Transmission Assumptions.”

²⁹⁶ Technology key is the unique collection of technologies that constitutes a specific vehicle, see Chapter 2.3.6.

Figure 3-8: Light-Duty 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. NHTSA uses information from sponsored research, CBI, and NASEM to determine DMCs

for fuel-saving technologies.²⁹⁷ NHTSA applies a learning factor and 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 2024 dollars, can be found in the LD Technologies Input File. Chapter 4 discusses how NHTSA applies the RPE and learning curves to technology DMCs.

This analysis uses absolute costs instead of relative costs, which were used in rulemaking analyses prior to 2020. NHTSA uses absolute costs to ensure the full cost of the transmission is removed when the Model applies hybrid technologies. The cost of adoption of SHEV technology is modeled by first removing the costs associated with existing powertrain systems, then applying the SHEV 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

NHTSA uses AT DMCs from recommended relative costs discussed in the NAS 2015 report and NAS-cited studies. Table 3-43 shows the LD costs for the AT with learning curve and RPE adjustments applied in the current analysis.

Unless otherwise noted, 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.²⁹⁸ In the cases of level two (L2) and level three (L3) transmissions, when not already included in the cost estimate, NHTSA adds 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.²⁹⁹ The NAS-reported AT9 cost is relative to the AT8 and does not account for the cost of the HEG technology. In the analysis, the AT9 is only equipped with level 2 HEG technology. Therefore, NHTSA calculates the costs for the AT9L2 by adding the cost estimate for one additional gear to the AT8L2 cost.³⁰⁰

For AT10 technologies, NHTSA uses DMCs from Table 8A.2a of the 2015 NAS report.³⁰¹ The NAS AT10 cost is relative to the AT8 and does not account for the cost of HEG technology. For the current LD 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.

²⁹⁷ 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 Institute for teardown studies evaluating mass reduction 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.

²⁹⁸ 2015 NAS report, at pp. 189, 298 – 99.

²⁹⁹ 2015 NAS report, at pp. 298 – 99.

³⁰⁰ 2015 NAS report, at pp. 298 – 99.

³⁰¹ 2015 NAS report, at pp. 298 – 99.

Table 3-43: Summary of LD Absolute Automatic Transmission Technology Costs for Automatic Transmissions, Including Learning Effects and Retail Price Equivalent in 2024\$

Name	Technology Pathway	2020	2022	2026	2030
AT5	Automatic Transmission	2,550	2,550	2,550	2,550
AT6	Automatic Transmission	2,569	2,569	2,569	2,569
AT7L2	Automatic Transmission	2,810	2,796	2,781	2,773
AT8	Automatic Transmission	2,683	2,683	2,683	2,683
AT8L2	Automatic Transmission	2,985	2,960	2,935	2,923
AT8L3	Automatic Transmission	3,238	3,199	3,159	3,140
AT9L2	Automatic Transmission	3,277	3,237	3,196	3,176
AT10L2	Automatic Transmission	3,277	3,237	3,196	3,176
AT10L3	Automatic Transmission	3,531	3,477	3,420	3,394

3.2.5.2. Continuously Variable Transmissions

Table 3-44 shows CVT costs with learning curve and RPE adjustments in 2024 dollars. The DMC for CVT and CVTL2 data comes from the 2015 NAS report Table 8A.2a.

Table 3-44: Summary of LD Absolute Transmission Costs for Continuously Variable Transmissions, Including Learning Effects and Retail Price Equivalent in 2024 Dollars

Name	Technology Pathway	2020	2022	2026	2030
CVT	Continuously Variable Transmission	2,900	2,894	2,884	2,876
CVTL2	Continuously Variable Transmission	3,127	3,117	3,100	3,087

3.2.5.3. Dual-Clutch Transmissions

Table 3-45 shows the absolute cost for DCTs with learning curve and RPE adjustments in 2024 dollars. The DMC for the DCTs come from the 2015 NAS report Table 8A.2a.³⁰²

Table 3-45: Summary of Absolute Transmission Costs for Dual-Clutch Transmissions, Including Learning Effects and Retail Price Equivalent for the Current Analysis in 2024 Dollars

Name	Technology Pathway	2020	2022	2026	2030
DCT6	Dual-Clutch Transmission	2,634	2,634	2,633	2,633
DCT8	Dual-Clutch Transmission	3,318	3,318	3,317	3,317

3.3. Hybrid Paths

The hybrid 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

³⁰² 2015 NAS report, at pp. 298 – 99.

range from engine stop-start to the hybridization of the powertrain (as in the case of a strong hybrids or SHEVs).

Unlike other technologies in the analysis, Congress placed specific limitations on how NHTSA considers alternative fueled vehicle fuel economy when determining maximum feasible CAFE standards; this impacts how NHTSA models electric and hybrid-electric technologies in the analysis. In determining maximum feasible fuel economy levels, Federal law provides that “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.”³⁰³ Accordingly, NHTSA imposes modeling restrictions to ensure that electric vehicle fuel economy is not considered in the analysis used for standard setting. NHTSA does not consider fully electric technologies (*i.e.*, BEVs and FCEVs) in the standard-setting (or constrained) analysis, and discussions of how those technologies were modeled are included only in relevant Final SEIS (unconstrained) documentation.

NHTSA implements these restrictions in the CAFE Model by using gasoline-only³⁰⁴ PHEV fuel economy values and by restricting ICE vehicles in a manufacturer’s fleet from converting to a BEV or a FCEV.³⁰⁵ The following discussion includes detail on how NHTSA models the constrained analysis used for standard setting, including a discussion of the electric range of considered hybridized technologies.

Hybridized vehicles have a partially electrified powertrain. Among the simpler configurations with the fewest hybrid components, micro hybrid technology (SS12V) uses a 12-volt system that simply restarts the engine from a stop without regenerative braking functionality. Mild HEVs use a 48-volt BISG system that restarts the engine from a stop with regenerative braking function. Mild HEVs are typically capable of subtle electric assist to the engine when accelerating from a standstill.

Strong hybrids (SHEVs) have higher system voltages compared to micro and mild hybrids and are capable of stop-start and regenerative braking function, electric motor assist to the engine at higher speeds, and, in many cases, have limited all-electric propulsion abilities. Please note that though SHEVs have limited all-electric propulsion abilities, electric propulsion is not the determining factor of whether a vehicle is a dual-fueled vehicle under 49 U.S.C. 32902(h). Rather, to qualify as a dual-fueled vehicle pursuant to 49 U.S.C. 32901(c), the vehicle must meet the minimum driving range specified at 49 CFR 538.5. Common SHEV powertrain architectures, classified by the interconnectivity of common hybridized 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 reflect PHEVs in the market today. PHEVs are restricted to gasoline-only function (*i.e.*, “charge sustaining” mode) in the standard-setting analysis.

Table 3-46 below shows an overview of these hybridized technologies and their designations. Like other technologies in these analyses, these technologies are not representative of any specific manufacturer’s design or architecture; instead, each individual hybridization technology encompasses the range of effectiveness and cost for these levels of hybridization technologies that exist in the market during the

³⁰³ 49 U.S.C. 32902(h).

³⁰⁴ NHTSA receives two databases of effectiveness values from the Autonomie modeling, including one with PHEV fuel economy values when operating on gasoline only (“charge sustaining” mode).

³⁰⁵ CAFE Model Documentation, at p. 36.

rulemaking timeframe. For example, the SHEVPS powertrain efficiency and cost are not intended to represent exactly a Toyota Prius or a Honda Accord Hybrid.

Table 3-46: Overview of Hybridization Technologies Used in the CAFE Model

Hybrid System	Technology Assignment
Micro Hybrid ^a	SS12V
Mild Hybrid ^b	BISG
Strong Hybrid	SHEVPS and SHEVP2
Plug-In Hybrid ^c	PHEV in 20- and 50-mile range variants
^a This system does not have engine assist or regenerative braking capabilities. ^b Mild Hybrid uses an engine-mounted BISG. ^c PHEVs in this analysis include both power-split (PS) and parallel (P2) hybrid architecture. PHEVs are restricted to gasoline-only function (<i>i.e.</i> , “charge sustaining” mode). See Table 3-47 and Table 3-48 below for further splits within each technology class.	

The cost effectiveness of hybridization technologies is based on both battery and non-battery components. The battery strongly influences the cost of some hybridized vehicles, particularly where the battery is a major source of energy for propulsion of the vehicle. Because developments in battery technology may apply to more than one category of hybridized vehicles, they are discussed collectively in Chapter 3.3.5; this subchapter covers battery-related topics that directly affect the costing of batteries for all types of hybridized vehicles that NHTSA considers. See further information on battery direct costs and learning in Chapter 3.3.5.1 and Chapter 3.3.5.3, respectively.

Non-battery hybridization components include propulsion components such as 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 convert mechanical energy to electrical energy for storage in the battery.

Non-battery hybridization components also include the power electronics that process and route electric power between the energy storage and propulsion components. More specifically, the power electronics components that NHTSA includes in the analysis are motor controllers, which issue complex commands to control torque and speed of the electric motors precisely; they also function as rectifiers, which convert and manage direct current (DC) and alternating current (AC) between the battery and the propulsion components. On-board battery chargers are also included in the analysis, as applicable, and are responsible for charging the PHEV battery from alternating current line power. Finally, DC/DC converters are included in the analysis to allow for different DC voltages within the vehicle’s system circuitry.

In addition, off-board chargers are charging devices that, when plugged into a PHEV, allow charging from the electric 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 are powered by a standard household 120V AC power outlet. AC Level 2 chargers can be installed residentially, at a workplace, or publicly and generally charges using between 208V and 240V AC, though some can charge

using as high as 277V AC.³⁰⁶ The process by which the CAFE Model prices non-battery components and adds/subtracts components as necessary to complete the powertrain architecture is discussed in Chapter 3.3.5.

The following subchapters discuss how each hybridization technology is defined in the CAFE Model for the LD analyses fleets and discusses the hybridization pathways that a vehicle can follow in response to CAFE standards or reference baseline regulatory scenarios. The subchapters also discuss how NHTSA assigns hybridized vehicle technologies to vehicles in the LD analysis fleets, any limitations on hybridization technology adoption, and the specific effectiveness and cost assumptions that NHTSA uses in the Autonomie Model and the CAFE Model analysis.

3.3.1. Hybrid Technologies

The CAFE Modeling system defines and utilizes technology pathways to simulate the logical progression of fuel-saving technologies across specific vehicle groupings – such as the transition from micro hybrids with stop-start to strong hybrid architectures. Technologies that share similar characteristics are grouped into cohorts, which NHTSA represents and interprets within the CAFE Model as discrete entities. By organizing these entities into linear pathways, the CAFE Model uses these pathways to define relations of mutual exclusivity between conflicting sets of technologies.

Table 3-47 lists every hybridization technology considered in the analysis,³⁰⁷ including a brief description and the acronyms NHTSA uses in the documentation and input files. For brevity, NHTSA refers to technologies by their acronyms in this subchapter.

Table 3-47: CAFE Model Light-Duty Vehicle Hybrid Path 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 Powertrain 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 a High Compression Ratio Cooled EGR 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

³⁰⁶ Such as the Primecom 80-amp Level 2 J1772 charger.

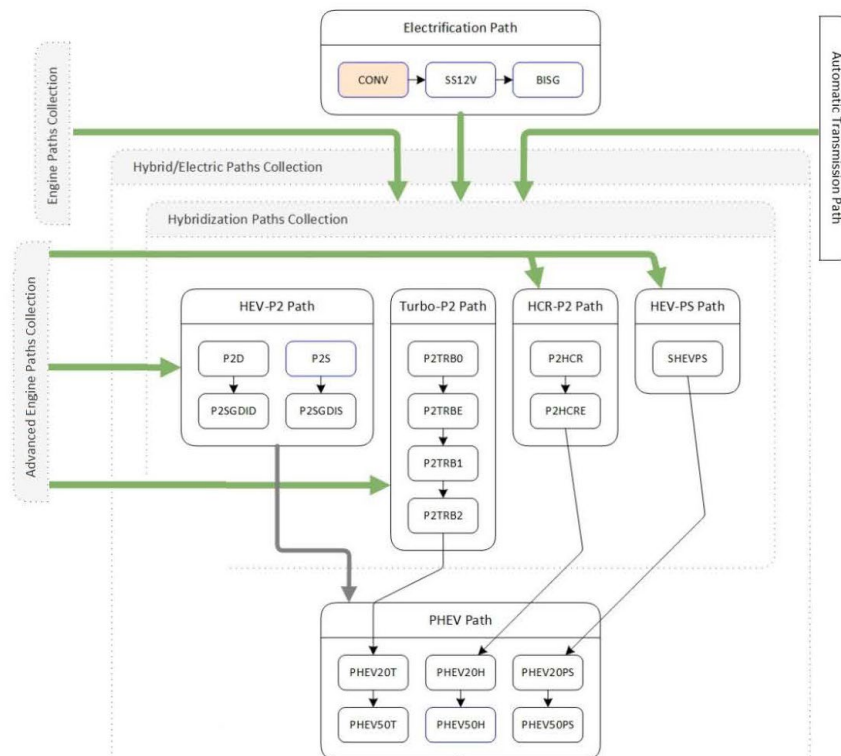
³⁰⁷ For the standard-setting analysis, BEVs and FCEVs are not considered, and PHEVs are considered to only operate on gasoline (*i.e.*, “charge sustaining” mode).

PHEV50T	Plug-In Hybrid-Electric Vehicle, Turbo Engine and 50-mile All-Electric Range
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

The hybridization paths in the CAFE Model for the LD analyses—listed above in Table 3-47—are illustrated in Figure 3-9 below.

As shown in Figure 3-9, the CONV technology is highlighted in orange. This technology identifier is used to denote whether a vehicle comes in with a CONV (*i.e.*, a vehicle that does not include any level of hybridization) and allows the Model to map to the Autonomie vehicle simulation database results properly. If multiple branches converge on a single technology, the subset of technologies disabled from adoption extend only up to the point of convergence.

Figure 3-9: Hybridization Paths in CAFE Model for LD



The CAFE Model defines the technology pathway for each type of hybridization grouping in a logical progression. Whenever the CAFE Model updates a vehicle model to incorporate any additional technology, such as with vehicle hybridization, modeling algorithms update both effectiveness and costs for the vehicle. In addition, all technologies on the different hybridization paths are mutually exclusive and are evaluated in parallel to one another.³⁰⁸ For example, the Model may evaluate plug-in hybrid technology prior to applying a mild or strong hybrid technology. NHTSA discusses the specific set of algorithms and rules further in the subchapters below. The CAFE Model Documentation includes more detailed discussions. The following subchapters discuss the specifications of each hybridization technology used in the analysis.

³⁰⁸ See the section on Technology Constraints (Supersession and Mutual Exclusivity) in the CAFE Model Documentation for additional discussions about path mutual exclusivity.

3.3.1.1. Micro Hybrids

Micro HEVs utilize SS12V technology, sometimes referred to as stop-start or idle-stop technology, and is considered the most basic hybrid system that facilitates fuel savings. In micro HEVs, the integrated starter 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 is cranked and starts again in response to throttle application or release of the brake pedal. The 12-volt battery used for the stop-start system is an improved unit compared to a traditional 12-volt battery. Specifically, it can produce more power, has an increased life cycle, and minimizes voltage drop on restart. This technology is beneficial to reduce fuel consumption when the vehicle frequently stops, such as in city driving conditions. However, this technology is limited in that it is not capable of regenerative braking, engine assist, or electric-only operation. SS12V can be applied to any vehicle technology classes, but it is restricted from being applied in combination to BISG, SHEVs, and PHEVs.

3.3.1.2. Mild Hybrids

Mild HEVs, sometimes referred to as P0 hybrids, utilize a BISG to provide idle-stop capability as well as regenerative braking function. This system uses a nominal 48-volt battery system with increased capacity over conventional automotive batteries. These higher voltages allow the use of a smaller, more powerful and efficient electric motor/generator, which replaces the standard alternator. In BISG systems, the motor/generator couples to the engine via belt, like a standard alternator layout. During engine restart, the BISG system functions as a motor and turns over the engine. In addition, the BISG can function as a generator, assisting vehicle braking and recovering braking energy while the vehicle slows down (regenerative braking). The BISG system is powerful enough to assist the vehicle when launching from a stop, as with P2/P3 mild hybrids.³⁰⁹ The CAFE Model assumes that all modeled mild HEVs are 48-volt systems with engine belt-driven motor/generators.

NHTSA does not include crank integrated starter generator (CISG) systems, sometimes referred to as P1 hybrids, in the analysis. A CISG typically has a 48-volt system with a motor/generator 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 modifications to integrate the powertrain architecture compared to BISG systems. The size of the motor/generator increases the overall length of the CISG powertrain, often causing packaging and integration issues, making it difficult for most vehicles to adopt CISG technology. The increased length of the powertrain may not fit in an existing vehicle design, and 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 the LD analyses. Chapter 3.3.4 discusses further details of the technology specification and effectiveness.

3.3.1.3. Strong Hybrids

Strong HEVs are engineered with a high-voltage source typically between 200-300 volts DC; this strong level of hybridization combines two methods of propulsion—the ICE and the electric machine—to reduce fuel consumption, increase powertrain performance, or both. The electric machine, sometimes referred to as a motor/generator (M/G), also captures energy from the vehicle during deceleration or braking that

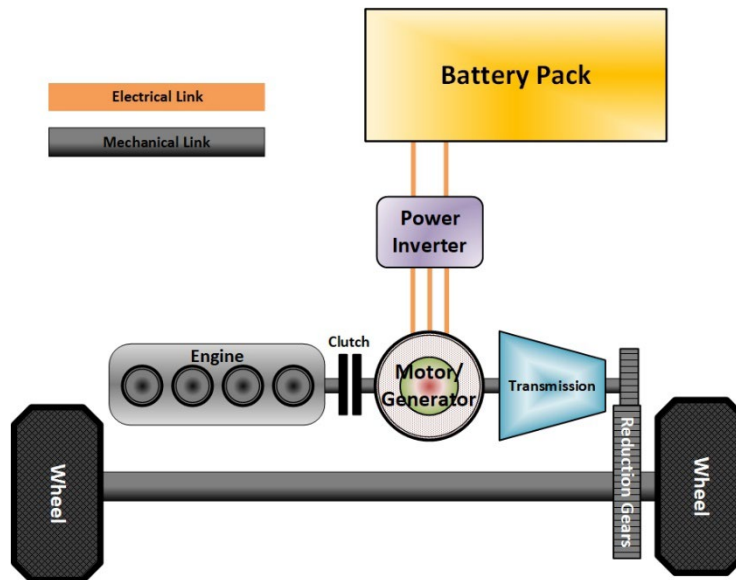
³⁰⁹ SEG Automotive, What is 48V/Mild Hybrid drive technology?, available at: <https://www.seg-automotive.com/48v/mild-hybrid-technology/> (accessed: Mar. 31, 2026).

would otherwise be released as heat. In addition, when the engine is running, the M/G can generate electricity for storage in the vehicle’s high-voltage on-board battery. This, along with the capability of providing launch and engine assist and limited electric-only operation, allows some SHEVs to reduce fuel consumption further 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 ICE off or to supplement engine power with the M/G 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 are included in the analysis: hybrids with parallel (P2) drivetrain architectures (SHEVP2)³¹⁰ and hybrids with series-parallel power-split architectures (SHEVPS).

SHEVP2s use a transmission-integrated M/G placed between the engine and gearing; a clutch allows for a decoupling of the M/G and transmission from the engine; Figure 3-10 below shows the SHEVP2 configuration. Though like the configuration of the CISG P1 mild hybrid system, generally, a P2 strong hybrid has a more powerful M/G and battery 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 M/G, and when combined with a transmission, it reduces gear-train losses relative to power-split or 2-mode hybrid systems. P2 SHEVs 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 3-10: Strong Hybrid Parallel (P2) Powertrain Architecture³¹¹



An important feature of the SHEVP2 system in the analysis is that it can be applied in conjunction with most conventional 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

³¹⁰ 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.

³¹¹ 2015 NAS report, at p. 133.

engine technology is less advanced than the conventional engine technology that the vehicle started with. For example, a vehicle in the 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 on the idea that though 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.

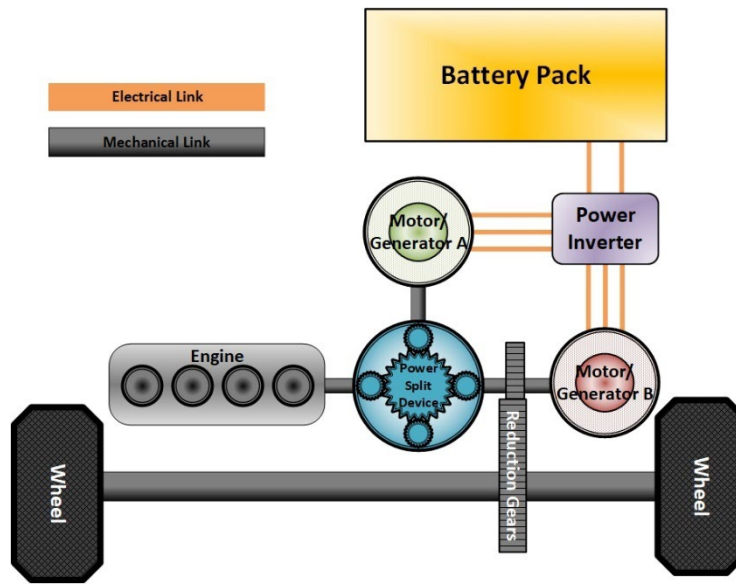
As discussed in Chapter 3.1.1.2.3, the SHEVP2 powertrain improves fuel economy by allowing the engine to spend more time operating at engine speed and load conditions that have high efficiency. The effectiveness improvement for SHEVP2 is reduced when combined with advanced engine technologies, which also improve fuel economy by broadening the range of engine speed and load conditions where the engine operates at high efficiency. 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 Section on Evaluation of Vehicle Technologies also discuss this logic.

Another strong hybrid architecture used in the analysis is the series-parallel power-split hybrid architecture (SHEVPS). In this powertrain, the traditional transmission is replaced with a single planetary gear set (*i.e.*, the power-split device or eCVT) and incorporates two motor/generators within its system. As seen in Figure 3-11, 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-B); M/G-A is also used as an electric motor to crank the engine. A second, more powerful motor/generator, Motor/Generator B (M/G-B) in the figure is responsible for propelling the SHEV and is referred to as the “drive motor.” 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.³¹² 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 function 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 3-11 below shows the SHEVPS architecture with the two motor/generators M/G-A and M/G-B. The analysis separates the two motor/generators to size each appropriately 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.

³¹² CAFE Analysis Autonomie Documentation, Chapter titled “Power-Split HEV.”

Figure 3-11: Strong Hybrid Power-Split (PS) Powertrain Architecture³¹³



Though enhanced by the hybrid components, SHEVP2 remains fundamentally like a CONV. In contrast, the SHEVPS is novel and considerably different than a CONV. Though these hybrid architectures are quite different, both hybrid types provide idle-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, though its cost is higher and engine power density is lower.³¹⁴

To expand on the hybrid powertrain configurations, Table 3-48 below shows the configuration of conventional engines and transmissions used with strong hybrids for the analysis. The SHEVPS powertrain configuration is paired with a planetary transmission (eCVT) and a full-time Atkinson engine.³¹⁵ This configuration is designed to maximize efficiency at the cost of reduced towing capability and real-world acceleration performance.³¹⁶ In contrast, the SHEVP2 powertrains are paired with an AT8L2 and can be paired with most conventional engines.³¹⁷

Table 3-48: Configuration of Strong Hybrid Architectures with Transmissions and Engines

CAFE Model Technologies	Transmission Options	Engine Options (LD)
SHEVPS	Planetary - eCVT	Full-Time Atkinson engine (Eng26)

³¹³ 2015 NAS report, at p. 133.

³¹⁴ Kapadia, J. *et al.*, Powersplit or Parallel - Selecting the Right Hybrid Architecture, *SAE International Journal of Alternative Power*, Vol. 6(1), pp. 68 – 76 (2017), available at: <https://doi.org/10.4271/2017-01-1154> (accessed: Mar. 31, 2026).

³¹⁵ The Engine NHTSA uses 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. NHTSA describes Eng26 in various tables in Chapter 3.1 as “HEV-PHEV Atkinson Cycle Engine 1.8L.”

³¹⁶ Kapadia, J. *et al.*, Powersplit or Parallel - Selecting the Right Hybrid Architecture, *SAE International Journal of Alternative Power*, Vol. 6(1), p. 68 (2017), available at: <https://doi.org/10.4271/2017-01-1154> (accessed: Mar. 31, 2026).

³¹⁷ NHTSA did not model SHEVP2s with HCRD, TURBOD, VTG, VTGE, VCR, TURBOAD, ADSL, or DSLI.

SHEVP2	AT8L2 or eCVT	Most Engines ³¹⁸
See further details in Chapter 3.3.4 Hybrid Electric 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 greater electric propulsion capability with a larger high-voltage battery pack with more energy storage, which allows PHEVs have a significantly greater AER than typical strong HEVs. 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 SHEVs. Depending on how these vehicles are operated, they could use electricity exclusively or operate like a SHEV in any particular mode of operation. For this analysis, only “charge sustaining” PHEV operation is considered.

Four PHEV technologies 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 for the model years covered in this rulemaking.

PHEV20PS and PHEV50PS can be thought of as SHEVPSs with a larger battery and the ability to drive longer distances with the engine 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 can travel in all-electric mode even at higher speeds and loads compared to PHEV20PS. NHTSA only considers “charge sustaining” PHEV operation in its standard-setting analysis.

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 PHEVx0H represents the HCR engine configuration. The PHEV versions of these hybrid architectures include larger batteries and motors to meet performance requirements at higher speeds and loads in both charge sustaining and all-electric modes. Table 3-49 below presents the different PHEV configurations used in this analysis. Chapter 3.3.4 includes further discussion of PHEV engine sizing, batteries, and electric motors.

Table 3-49: Configuration of Plug-in Hybrid Architectures with Transmissions and Engines

CAFE Model Technologies	Transmission Options	Engine Options
PHEV20H	Planetary - eCVTs	HCR engine; 20-mile AER
PHEV20T	AT8L2	Turbo-charged engines; 20-mile AER

³¹⁸ Eng1, Eng5b, Eng12, Eng13, Eng18, Eng32, Eng33, Eng36, Eng37, and Eng41. See Chapter 3.1.3 for these engine specifications.

PHEV20PS	Planetary - eCVTs	Full-Time Atkinson Engine; 20-mile AER
PHEV50PS	Planetary - eCVTs	Full-Time Atkinson Engine; 50-mile AER
PHEV50H	Planetary - eCVTs	HCR engine; 50-mile AER
PHEV50T	AT8L2	Turbo-charged engines; 50- mile AER
See further details in Chapter 3.3.4 Hybrid Electric Effectiveness.		

3.3.2. Assigning Hybrid Technologies in the Analysis Fleet

Hybridization technologies present in the analysis fleet are identified as the starting point for this analysis. Technology assignments are based on manufacturer-submitted CAFE compliance information, publicly available technical specifications, manufacturer marketing brochures, articles from reputable media outlets, and data from other market data materials.³¹⁹

Table 3-47, in Chapter 3.3.1, lists every hybridization technology considered in the analysis, including a brief description of the technology and the acronym that NHTSA uses in the documentation and input files.

Table 3-50 below expands on these hybridization technologies and gives the initial penetration rates of eligible hybridization technologies in the MY 2024 analysis fleet. Over half the LD fleet has some level of hybridization.

Table 3-50: Penetration Rate of Hybridization Technologies in the MY 2024 Light-Duty Fleet

Hybridization Technology	Sales Volume with this technology	Penetration Rate in the MY 2024 Analysis Fleet
Conventional Only	2,676,769	19.53%
SS12V	8,630,909	62.97%
BISG	582,001	4.25%
SHEVP2	433,158	3.16%
SHEVPS	992,567	7.24%
PHEV20PS	11,248	0.08%
PHEV20H	56,597	0.41%
PHEV20T	267,743	1.95%
PHEV50PS	15,027	0.11%
PHEV50H	30,914	0.23%
PHEV50T	9,287	0.07%
TOTAL	13,706,220	100%

³¹⁹ Rho Motion and Benchmark Mineral Intelligence proprietary data.

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 are used to identify the presence of these technologies on vehicles in the fleets. As with all technology assignments, micro and mild hybrid technologies are only assigned if NHTSA could confirm technological presence with manufacturer compliance data, manufacturer brochures, or data sources discussed above.

3.3.2.2. Strong Hybrids

Strong hybrid technology assignments in the Market Data Input File are based on SHEVPS and SHEVP2 powertrain architectures. Chapter 3.3.1.3 presents a discussion of differences in architecture between these technologies. When possible, manufacturer specifications are used to identify the strong hybrid architecture type. In the absence of more sophisticated information, NHTSA determines hybrid architecture by the number of electric “traction” motors on the main drive axle; hybrid powertrains with one electric motor on the main drive axle are designated “P2,” and those with two electric motors on the main drive axle “PS.”

3.3.2.3. Plug-In Hybrids

Plug-in hybrid technologies that NHTSA assigns in the analysis fleets include PHEV20PS/20H/20T and PHEV50PS/50H/50T. NHTSA assigns vehicles with an electric-only range of 40 miles or less as PHEV20 and assigns those with a range above 40 miles as PHEV50. These two ranges are appropriate to represent most of the PHEVs currently in the market when modeling cost and benefits. These ranges are compared against a combination of market review for PHEVs and reports showing that they are typical for short commutes.^{320,321} NHTSA assigns vehicles as PHEV20T/50T if the engine is turbocharged³²² and assigns vehicles that qualify for full-time Atkinson cycle engines, such as the Toyota Prius Prime, as PHEV20PS/50PS.

The CAFE Model Documentation Section on the Calculation of Vehicle’s Fuel Economy presents additional information on the calculation methodology for PHEVs.

3.3.3. Hybrid Adoption Features

NHTSA applies several adoption features to the hybrid technologies, and the hybridized technology path logic dictates how vehicles could adopt different levels of hybridization technology in the Model. Figure 3-9 in the previous subchapter shows the hybridization technology pathways, and each of the pathways are discussed in detail within each technologies’ subchapter below. Broadly speaking, more advanced levels of hybridization supersede all prior levels, while certain technologies within each level are mutually exclusive. NHTSA models (from least to most hybridized) micro hybrids, mild hybrids, strong hybrids, and plug-in hybrids.³²³

³²⁰ Perks, R., & Raborn, C., Driving Commuter Choice in America: Expanding Transportation Choices Can Reduce Congestion, Save Money and Cut Pollution, NRDC IP.13-06A, New York, NY: Natural Resources Defense Council (2013), available at: <https://www.nrdc.org/sites/default/files/driving-commuter-choice-IP.pdf> (accessed: Mar. 31, 2026).

³²¹ DOE, FOTW #1047, September 17, 2018: Daily Vehicle Miles Traveled Varies With the Number of Household Vehicles, last revised: Sept. 17, 2018, available at: <https://www.energy.gov/eere/vehicles/articles/fotw-1047-september-17-2018-daily-vehicle-miles-traveled-varies-number> (accessed: Mar. 31, 2026).

³²² See Chapter 3.1.1.2.2 for more information on turbocharged engines in the analysis.

³²³ See CAFE Model Documentation for additional description of how path logic is applied.

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 is manufactured by a manufacturer that has indicated that their future product plans will likely not include the technology. NHTSA expands on the specific criteria for SKIP logic for each applicable hybridization 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, NHTSA models 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.

Chapter 3.4 later 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 hybridization 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 3-9 under Chapter 3.3.1. The pathway consists of a linear progression starting with a CONV—absent any hybridization technology—which is superseded by SS12V, which, in turn, is superseded by BISG. Vehicles can adopt micro and mild hybrid technology only if the vehicle did not already have a more advanced level of hybridization.

3.3.3.2. Strong Hybrids

The SHEV technologies in the analysis include two architectures: series-parallel power-split powertrains (SHEVPS) and parallel powertrains (SHEVP2SGDID, SHEVP2SGDIS, P2S, P2D, P2TRB0, P2TRB1, P2TRB2, P2TRBE, P2HCR, and P2HCRE). Table 3-50 presents additional SHEV technology details.

The adoption features that NHTSA applies 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. 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 a variety of plug-in hybrid 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—considering relative cost effectiveness. For SHEVPS technology, the existing engine is replaced with a full-time Atkinson cycle engine.³²⁴

SKIP logic is used to constrain adoption for SHEVPS and PHEV20/50PS. These technologies are “skipped” for vehicles with engines³²⁵ that meet one of the following conditions:

³²⁴ Designated Eng26 in the list of engine map models used in the analysis. See Chapter 3.1.1.2.3 for more information.

³²⁵ This refers to the engine assigned to the vehicle in the 2022 baseline fleet.

- The engine belongs to an excluded manufacturer;³²⁶
- The engine belongs to a pickup truck (*i.e.*, the engine is on a vehicle assigned the “pickup” body style);
- The engine’s peak HP 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 like those for the SKIP logic that NHTSA applies 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 unrealistic.

No SKIP logic applies to SHEVP2. NHTSA believes that this type of hybridized powertrain is sufficient to meet all 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.^{327,328}

3.3.3.3. Plug-In Hybrids

Plug-in hybrid-electric vehicle (PHEV) technologies include PHEV20PS/20H/20T and PHEV50PS/50H/50T, and they supersede the micro, mild, and strong hybrids. For the CAFE Models runs for this analysis, PHEVs are the end of the hybridization pathway. Plug-in hybrid technology paths are also mutually exclusive,³²⁹ with the PHEV20x³³⁰ technologies able to progress to the PHEV50x³³¹ technologies.

LD PHEV technologies include series-parallel power-split powertrains (PHEVx0PS)³³² and parallel powertrains (PHEVx0T³³³ and PHEVx0H³³⁴).³³⁵ Table 3-50 presents additional PHEV technology details. There are no other technological constraints for PHEVs for the LD analysis, and the Model applies PHEV powertrains if it deems them cost effective. However, per the statutory restrictions, NHTSA is only able to consider the gas-only fuel economy for PHEVs in this analysis.

³²⁶ Excluded manufacturers are those that have indicated that their future product plans will not include the technology and, for SHEVPS and PHEV20/50PS include BMW, Daimler, and JLR.

³²⁷ Buchholz, K., Toyota Tundra: V8 Out, Twin-Turbo Hybrid Takes Over, last revised: Sept. 22, 2021, available at: <https://www.mobilityengineeringtech.com/component/content/article/45145-sae-ma-06782> (accessed: Mar. 31, 2026).

³²⁸ Visnic, B., Hybridization the Highlight of Ford’s All-New 2021 F-150, last revised: July 1, 2020, available at: <https://www.mobilityengineeringtech.com/component/content/article/44565-sae-ma-03885> (accessed: Mar. 31, 2026).

³²⁹ Per the defined (applicable) technology pathways, PHEVx0PS, PHEVx0H, and PHEVx0T technologies are considered mutually exclusive.

³³⁰ PHEV20x is used as an abbreviation for the variations of PHEVs with an AER of 20 miles (*i.e.*, for PHEV20PS, PHEV20T and PHEV20H).

³³¹ PHEV50x is used as an abbreviation for the variations of PHEVs with an AER of 50 miles (*i.e.*, for PHEV50PS, PHEV50T and PHEV50H).

³³² PHEVx0PS is used as an abbreviation for the variations of power-split PHEVs with either AER of 20 or 50 miles (*i.e.*, PHEV20PS and PHEV50PS).

³³³ PHEVx0T is used as an abbreviation for the variations of P2 turbo PHEVs with either AER of 20 or 50 miles (*i.e.*, PHEV20T and PHEV50T).

³³⁴ PHEVx0H is used as an abbreviation for the variations of HCR PHEVs with either AER of 20 or 50 miles (*i.e.*, PHEV20H and PHEV50H).

³³⁵ Per the defined (applicable) technology pathways, PHEVx0PS, PHEVx0H, and PHEVx0T technologies are considered mutually exclusive.

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 and PHEV20H/50H technologies, while the Model applies an eCVT transmission for all PHEV20PS/50PS technologies. A vehicle adopting PHEV20PS/50PS receives a hybrid full-time Atkinson cycle engine,³³⁶ a vehicle adopting PHEV20H/PHEV50H receives an HCR engine and a vehicle adopting PHEV20T/50T receives a TURBO1 engine.

3.3.4. Hybrid Effectiveness

NHTSA considers a range of hybridization technologies that, when modeled, result in varying levels of effectiveness at reducing fuel consumption. The modeled hybridization technologies include micro hybrids, mild hybrids, strong hybrid architectures, and plug-in hybrid architectures with two different AERs. Each hybridization technology consists of many complex subsystems with unique component characteristics and operational modes. The systems that contribute to the effectiveness of a hybridized powertrain in the analysis include the vehicle’s battery, electric motor/generator(s) (“M/G(s)”), power electronics, and accessory loads. NHTSA discusses 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 powertrain models, including hybrid powertrains. 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 hybridization technology.

As NHTSA discusses 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,³³⁷ and the modeled hybrid vehicle 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 is completed, all criteria will be met, and some may be exceeded as a necessary consequence of meeting others.³³⁸

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. Though 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. Though the resizing algorithm for all vehicles must satisfy the same performance criteria, the algorithm for some electric powertrains must also allow those hybridized 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.

³³⁶ 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.

³³⁷ Chapter titled “Vehicle Sizing Process” of the CAFE Analysis Autonomie Documentation.

³³⁸ See chapter titled “Vehicle Sizing Process” in the CAFE Analysis Autonomie Documentation for more information on how sizes hybrid powertrains.

To establish the effectiveness of the technology packages, Autonomie simulates the vehicles' performance on compliance test cycles.^{339,340,341} For vehicles with CONVs and micro hybrid powertrains, Autonomie simulates the vehicles using the 2-cycle test procedures and guidelines.³⁴² 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, as described in SAE J1711. SAE J1711 also provides test cycle guidance for testing specific to plug-in HEVs.³⁴³ To conform with analytical constraints imposed by Federal statute, the CAFE Model evaluates PHEV modeled effectiveness by assuming AER is exhausted and the vehicle functions like a SHEV.

The range of effectiveness for the hybridization 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 results in some modeled effectiveness values being close to real-world measured values and some modeled values that 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 NAS 2015 recommendation to use full-vehicle modeling supported by the application of lumped improvements at the sub-model level.³⁴⁴ 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 component selection within the Model. The details of the approach are discussed further in Chapter 3.3.4.1. Figure 3-12 below presents the values of technology effectiveness for hybrid technologies.

³³⁹ EPA, How Vehicles are Tested, last revised: 2023, available at: https://www.fueleconomy.gov/feg/how_tested.shtml (accessed: Mar. 31, 2026).

³⁴⁰ Chapter titled "Test Procedure and Energy Consumption Calculations" of the CAFE Analysis Autonomie Documentation.

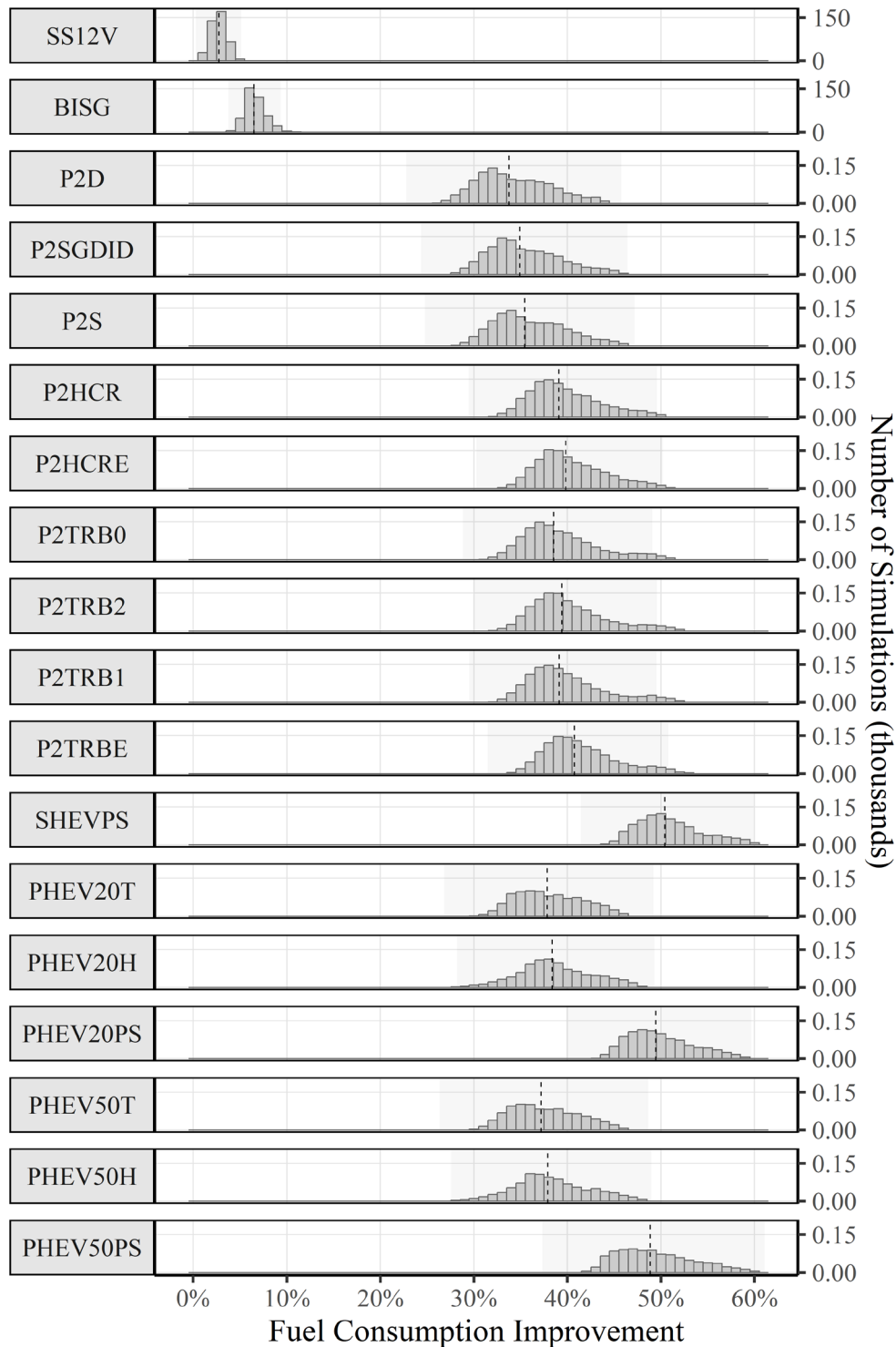
³⁴¹ Good, D., EPA Test Procedure for Electric Vehicles and Plug-in Hybrids, DRAFT Summary, Washington, D.C.: EPA (2017), available at: <https://fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf> (accessed: Mar. 31, 2026).

³⁴² 40 CFR part 600.

³⁴³ 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.

³⁴⁴ 2015 NAS report, at p. 292.

Figure 3-12: Light-Duty Hybridization Technology Effectiveness Values for All Vehicle Technology Classes



The following subchapters discuss the data that NHTSA uses to model each hybrid vehicle component and the Autonomie models that NHTSA uses to simulate the effectiveness of each hybridized powertrain technology.

3.3.4.1. Batteries, Electric Motor/Generators, Power Electronics, and Accessories

Autonomie determines the effectiveness of each hybridized powertrain type by modeling the basic components for each powertrain and then combines the components modularly to determine the overall efficiency of the entire powertrain. The basic components that comprise a hybridized powertrain in the analysis include the battery, electric motor/generators, power electronics, and accessory loads.

Autonomie identifies components for each hybridized powertrain type and then interlinks those components to create a powertrain architecture. Autonomie models each hybrid powertrain architecture and provides an effectiveness value for each architecture. For example, Autonomie determines a hybrid vehicle’s overall efficiency, such as that of a SHEVP2, by considering the efficiencies of the battery, the electric traction drive system (ETDS, the electric machine and power electronics), and mechanical power transmission devices and combining it with the conventional combustion engine, transmission, and related powertrain and components.

Autonomie employs a set of electric motor efficiency maps created by Oak Ridge National Laboratory (ORNL): one for a traction motor and an inverter and the other for a motor/generator and inverter.³⁴⁵ The electric motor efficiency maps, created from production vehicles as shown in Table 3-51 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.³⁴⁶ Specifically, Argonne scales the efficiency maps, specific to powertrain type, to have total system peak efficiencies ranging from 96-98 percent³⁴⁷—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).³⁴⁸ Table 3-51 shows the electric machine efficiency map sources for the different LD powertrain configurations.

³⁴⁵ Bures T.A. *et al.*, Evaluation of the 2007 Toyota Camry Hybrid Synergy Drive System, Report No. ORNL/TM-2007/190, revised ORNL/TM-2007/190, Oak Ridge, TN: OSTI, (2008), available at: <https://www.osti.gov/servlets/purl/928684/> (accessed: May 27, 2026); Oak Ridge National Laboratory, Annual Progress Report for the Power Electronics and Electric Machinery Program (2011).

³⁴⁶ See CAFE Analysis Autonomie Documentation, Chapter titled “Electric Machine Efficiency Maps.”

³⁴⁷ See CAFE Analysis Autonomie Documentation, Chapter titled “Electric Machine Peak Efficiency Scaling.”

³⁴⁸ Bures T.A. *et al.*, Evaluation of the 2007 Toyota Camry Hybrid Synergy Drive System, ORNL: Washington, D.C. (2008), available at: <https://doi.org/10.2172/928684> (accessed: May 27, 2026); Oak Ridge National Laboratory, ORNL/TM-2011/263, Oak Ridge, TN: ORNL (2011), available at: https://digital.library.unt.edu/ark:/67531/metadc845565/m2/1/high_res_d/1028161.pdf (accessed: May 27, 2026).

Table 3-51: Electric Machine Efficiency Map Sources for Different Powertrain Configurations

Powertrain Type	Source of Efficiency Map for Motor1 (Traction Motor) + Inverter	Source of Efficiency Map for Motor2 (Motor/Generator) + Inverter
SS12V	Camry HEV EM1 data from ORNL	N/A
BISG	Camry HEV EM1 data from ORNL	N/A
SHEVP2	N/A	Sonata HEV EM2 data from ORNL
SHEVPS, PHEV20	Camry HEV EM1 data from ORNL	Camry HEV EM2 Data from ORNL
PHEV50	Camry HEV EM1 data from ORNL	Sonata HEV EM2 Data from ORNL

Beyond the powertrain components, Autonomie considers electric accessory devices that consume energy and affect overall vehicle effectiveness on the 2-cycle test. This includes radiator fans, 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, the electrical load for fuel economy compliance testing is repeatable because EPA’s fuel economy test procedures control for these factors. Accessory loads during test cycles do vary by powertrain type and vehicle technology class, because distinctly different powertrain components and vehicle masses consume different amounts of energy.

Different vehicle types within the analysis fleet have varying accessory electrical power demand. For example, vehicles with different motor and battery sizes require different sizes of electric cooling pumps and fans to manage component temperatures optimally. Autonomie has built-in models that can simulate these varying subsystem electrical loads. However, NHTSA uses 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. NHTSA expects that fixed accessory load values have, on average, similar impacts on effectiveness as found on actual manufacturers’ systems. This approach is in line with the past analyses.^{349,350} NHTSA aggregates electrical accessory load modeling assumptions for the different powertrain types (hybridized and conventional) from data from the Draft TAR, EPA Proposed Determination,³⁵¹ data from manufacturers,³⁵² research and development data from DOE’s Vehicle Technologies Office,^{353,354,355} and DOT-sponsored vehicle benchmarking studies completed by Argonne’s

³⁴⁹ Technical Assessment Report, July 2016, Chapter 5.

³⁵⁰ EPA Proposed Determination TSD, Nov. 2016, at pp. 2 – 270.

³⁵¹ EPA Proposed Determination TSD, Nov. 2016, at pp. 2 – 270.

³⁵² Alliance of Automobile Manufacturers Comments on Draft TAR, at p. 30.

³⁵³ DOE, Electric Drive Systems Research and Development, available at: <https://www.energy.gov/eere/vehicles/electric-drive-systems-research-and-development> (accessed: Apr. 29, 2026).

³⁵⁴ Argonne National Laboratory, Advanced Mobility Technology Laboratory (AMTL), available at: <https://www.anl.gov/taps/advanced-mobility-technology-laboratory> (accessed: Apr. 29, 2026).

³⁵⁵ DOE’s lab years are 10 years ahead of manufacturers’ potential production intent (e.g., 2020 lab year correlates with vehicle MY 2030).

AMTL, with vehicles such as the Toyota RAV4 Prime and Nissan Leaf.^{356,357} These assumptions are provided below in Table 3-52.³⁵⁸

Table 3-52: 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
Compact	LD Base	250	275	275
Compact	LD Premium	300	325	325
Mid-size	LD Base	250	275	275
Mid-size	LD Premium	300	325	325
Small SUV	LD Base	275	300	300
Small SUV	LD Premium	325	350	350
Mid-size SUV	LD Base	275	300	300
Mid-size SUV	LD Premium	325	350	350
Pickup	LD Base	275	300	300
Pickup	LD Premium	325	350	350

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 systems is attributable to the amount of fuel saved during the engine idling period on the 2-cycle test. The CAFE Analysis Autonomie Documentation presents additional discussion of the SS12V system models.³⁵⁹

Micro hybrid systems normally do not provide propulsion assist, so this technology has little to no impact on the vehicle performance metrics. Autonomie does not resize the powertrain 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.

³⁵⁶ Iliev, S. *et al.*, Vehicle Technology Assessment, Model Development, and Validation of a 2021 Toyota RAV4 Prime, Report No. DOT HS 813 356, NHTSA: Washington, D.C., (2022), available at: https://downloads.regulations.gov/NHTSA-2023-0022-0010/attachment_6.pdf (accessed: Mar. 31, 2026).

³⁵⁷ Jehlik, F. *et al.*, Vehicle Technology Assessment, Model Development, and Validation of a 2020 Chevrolet Bolt, (2022), Report No. DOT HS 813 351, National Highway Traffic Safety Administration.

³⁵⁸ See ANL - Summary of Main Component Performance Assumptions_NPRM_2206 and ANL - All Assumptions_Summary_NPRM_2206.xlsx, available in the rulemaking docket by filtering for Supporting & Related Material.

³⁵⁹ See Chapters “Electric Machines Efficiency Maps” and “Conventional Powertrain (Conventional/Micro-12V/Mild Hybrid BSIG)” of the CAFE Analysis Autonomie Documentation.

3.3.4.3. Mild Hybrids

The mild hybrid system in Autonomie is a 48V BISG.³⁶⁰ Mild hybrid vehicles provide idle-stop function and capture some braking energy (regenerative braking). Though mild hybrids can provide 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 LD analysis, a BISG system uses a 10-kW motor/generator paired with a 403-Wh battery pack to approximate mild hybrid systems found in the marketplace.³⁶¹ The specification of this system is provided in the Autonomie Input and Assumptions Description Files.³⁶²

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. Like 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

This analysis considers two strong hybrid architectures: 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 M/Gs, and an engine, and the Model allows for various interactions between these components. 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. A detailed discussion of the SHEVPS and SHEVP2 modeling and validation are provided in the CAFE Analysis Autonomie Documentation.³⁶³ Autonomie full-vehicle models representing the strong hybrids are based on vehicle benchmarking test data.

Power-split hybrids utilize a full-time Atkinson mode engine, two M/Gs, 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 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

³⁶⁰ These are 48 V DC electrical systems.

³⁶¹ Colwell, K.C., The 2019 Ram 1500 eTorque Brings Some Hybrid Tech, If Little Performance Gain, to Pickups, last revised: Mar. 14, 2019, available at: <https://www.caranddriver.com/reviews/a22815325/2019-ram-1500-ectorque-hybrid-pickup-drive> (accessed: Mar. 31, 2026).

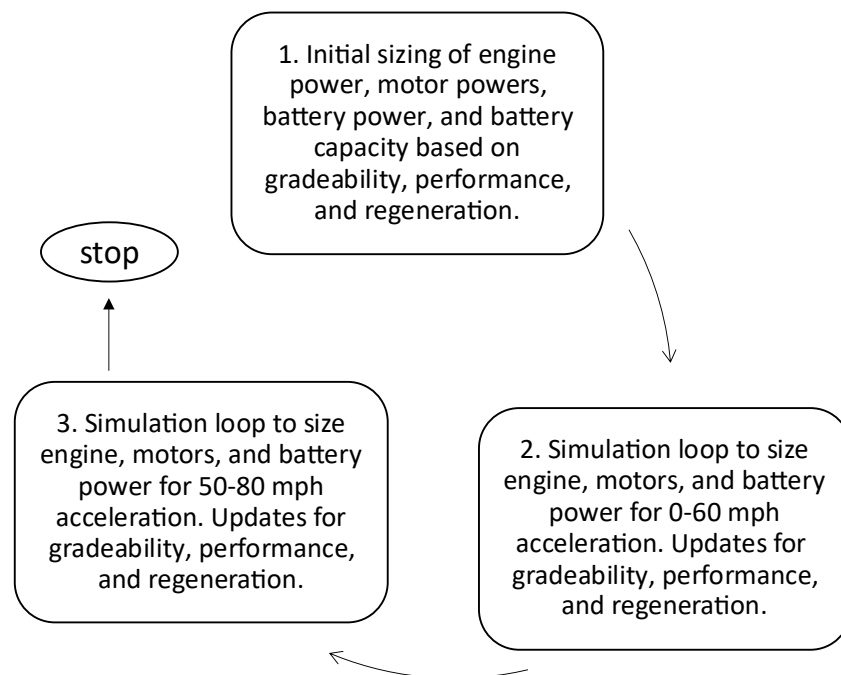
³⁶² See ANL – Summary of Main Component Performance Assumptions_NPRM_2206 and ANL – All Assumptions_Summary_NPRM_2206.xlsx, available in the rulemaking docket by filtering for Supporting & Related Material.

³⁶³ CAFE Analysis Autonomie Documentation, Chapters “Power-Split HEV (Split HEV)” and “Autonomie Validation.”

- 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 are 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 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 updated for gradeability performance and regeneration, if necessary. Figure 3-13 below shows the general steps of the SHEVPS sizing algorithm. Detailed descriptions are available in the CAFE Analysis Autonomie Documentation.

Figure 3-13: Simplified SHEVPS Sizing Algorithm in Autonomie



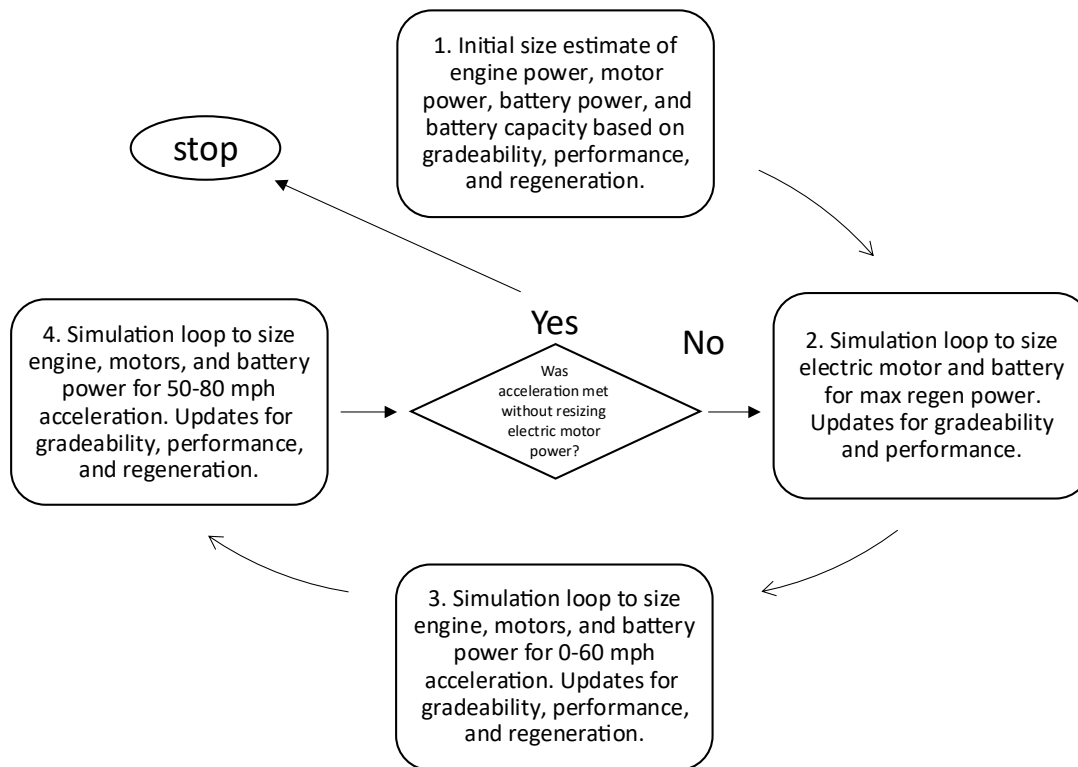
The SHEVP2 uses a combustion engine and a multi-speed transmission-integrated electric motor (EM1). This SHEVP2 allows most engines and advanced speed transmissions to integrate with an electric motor. To minimize the number of Autonomie simulations for combinations of engines and transmissions for all 10 vehicle classes,³⁶⁴ NHTSA uses the AT8L2 as the only transmission that can be integrated with SHEVP2. Manufacturers have continued to increase gear counts from the common 5- and 6-speed gears while improving transmission internals (*i.e.*, the architecture, gears, bearings, seals, pumps, type of gear finishing, *etc.*, within the transmission). These modern improvements are carried into the SHEVP2 architecture. In MY 2024, over 50 percent of the LD fleet had transmissions with seven gears or

³⁶⁴ For this analysis there are over 150,000 simulation results for all 10 vehicles classes. That number does not include the simulations associated with sizing of components for different powertrains.

higher.³⁶⁵ In addition, the higher geared 8-speed AT enables the maximization of engine efficiency by allowing the engine to operate in a more efficient region as compared to a lower geared transmission. These benefits are further discussed in Chapter 3.2.

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 uses a simulation loop to find a more precise value of regenerative braking power generated in the 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 returns to the regenerative braking loop and subsequently all other loops until all components are optimized. Figure 3-14 below shows a simplified sizing algorithm for SHEVP2s.

Figure 3-14: 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

³⁶⁵ See Chapter 3.2.2 for a more detailed breakdown of transmission penetration rates.

nameplate.^{366,367} 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.³⁶⁸

In addition, NHTSA limits adoption of some advanced engine technologies with strong hybrids in cases where the hybridization technology has little effectiveness benefit beyond the benefit of the advanced engine system and substantially increases costs. Specifically, NHTSA does not model strong hybrid technologies with TURBOD, HCRD, VCR, VTG, VTGE, TURBOAD, ADSL, or DSLI engines. NHTSA believes that manufacturers would not consider these combinations because the combination of hybridization and advanced engine technologies are not as cost effective as other technologies.

3.3.4.5. Plug-in Hybrids

The effectiveness of the PHEV systems is dependent on the vehicle’s battery pack size as well as other fuel-economy-improving technologies on the vehicle (*e.g.*, AERO and mass reduction technologies).

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, electric 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.³⁶⁹ However, because 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.^{370,371} Though PHEVs powertrains are *sized* using algorithms that are in part based on electric-only operation per these drive cycles, the final fuel economy values are based strictly on gas-only operation.

NHTSA classifies PHEVs into six technology categories: (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.

³⁶⁶ For example, the 2024 4WD Ford F-150 uses a turbo-charged 3.5 L engine for its hybrid and is an option for its non-hybrid model.

³⁶⁷ For example, the 2024 Hyundai Elantra uses a turbo-charged 1.6 L engine for its hybrid and is an option for its non-hybrid model.

³⁶⁸ Chapter “Vehicle Sizing Process” of the CAFE Analysis Autonomie Documentation.

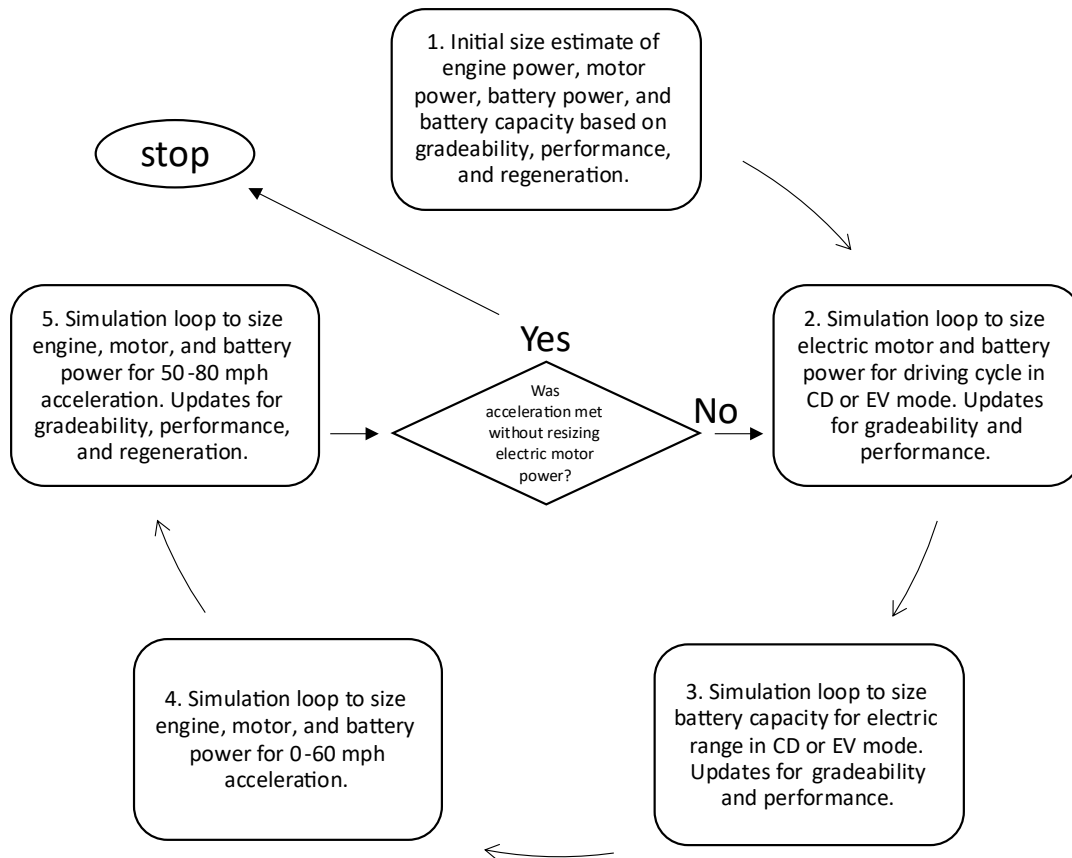
³⁶⁹ CAFE Analysis Autonomie Documentation, titled “9.3.1.3 Parallel HEV (Par HEV) Sizing Algorithm.”

³⁷⁰ Battery sizing and the definition of the combined 2-cycle test’s AER is discussed in detail in Chapter “Battery Performance and Cost Model (BatPaC)” of the CAFE Analysis Autonomie Documentation.

³⁷¹ Argonne has incorporated SAE J1711, Recommended Practice for Measuring Exhaust Emissions and Fuel Economy of Hybrid-Electric Vehicles, Including Plug-In Hybrid Vehicles, into the Autonomie modeling.

The PHEV20x³⁷² and PHEV50x³⁷³ resizing algorithms are functionally equal and differ only in the type of electric mode driving cycle simulated in each (UDDS for PHEV20x, or US06 for PHEV50x). 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 PHEV20x, the power of the motor/generators and battery must be sized to propel the vehicle through the UDDS cycle in “CD mode.” In this mode, the M/G alone propels the vehicle except during high power demands, at which point the engine may turn on and provide propulsion assistance. The PHEV50x 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 3-15 below shows the general steps of the PHEV sizing algorithm. Detailed steps are presented in the CAFE Analysis Autonomie Documentation.³⁷⁴

Figure 3-15: Simplified PHEV Sizing Algorithm in Autonomie



³⁷² PHEV20x is used as an abbreviation for the variations of PHEVs with an AER of 20 miles (*i.e.*, for PHEV20PS, PHEV20T and PHEV20H).

³⁷³ PHEV50x is used as an abbreviation for the variations of PHEVs with an AER of 50 miles (*i.e.*, PHEV50PS, PHEV20T, and PHEV50H).

³⁷⁴ CAFE Analysis Autonomie Documentation, Chapters titled “Parallel PHEV Sizing Algorithm” and “Voltec PHEV (Extended Range) Vehicle Sizing Algorithm.”

The Autonomie sizing algorithm is automated, and any change in one of the component checks in the steps shown in Figure 3-16 requires the components to be reevaluated and sized appropriately.

3.3.5. Hybrid Costs

The total cost to hybridize a vehicle in this analysis is based on the vehicle’s battery and non-battery hybridization component costs and requirements, as well as the update to or removal of the traditional powertrain components to build the hybridized powertrain. The presence of a battery in a vehicle is not the determining factor for whether a vehicle is a dedicated or dual-fueled vehicle under Chapter 329 because all vehicles have batteries of some form. This subchapter provides insight into how the costs for batteries used in hybrid vehicles are determined and how those costs are used in this analysis.

3.3.5.1. Base Year Battery Pack Costs and Modeling

NHTSA works collaboratively with the experts at Argonne to generate automotive battery costs using BatPaC—a model designed to calculate battery costs. 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 a hybridized powertrain. The BatPaC battery cost estimates are generated for a *base year*, being MY 2022 for the current analysis; the assumed BatPaC inputs, discussed below, fairly characterize the state of the market for MY 2022.

To reflect how battery costs—across different hybridized powertrains—could decrease over the timeframe considered, NHTSA applies a learning rate to the BatPaC-generated DMCs. Broadly, the learning rate that NHTSA applies to batteries reflects middle-of-the-road year-over-year improvements through MY 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. The rest of this subsection focuses on *base year* battery costs only. The following subchapters discuss Argonne’s process for generating base year battery pack DMCs.

BatPaC is software designed for policy-makers and researchers who are interested in estimating the cost of lithium-ion batteries after they have reached a mature state of development and are being manufactured in high volumes.³⁷⁵ The BatPaC 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 different levels of vehicle hybridization as well as alternative battery 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.

NHTSA uses BatPaC version 5.0 (March 2022 release) to estimate the base year battery cost for hybrid vehicle technologies for LDVs.³⁷⁶ Running individual BatPaC simulations for each full-vehicle simulation and updating the powertrain to a hybridized powertrain is computationally intensive and

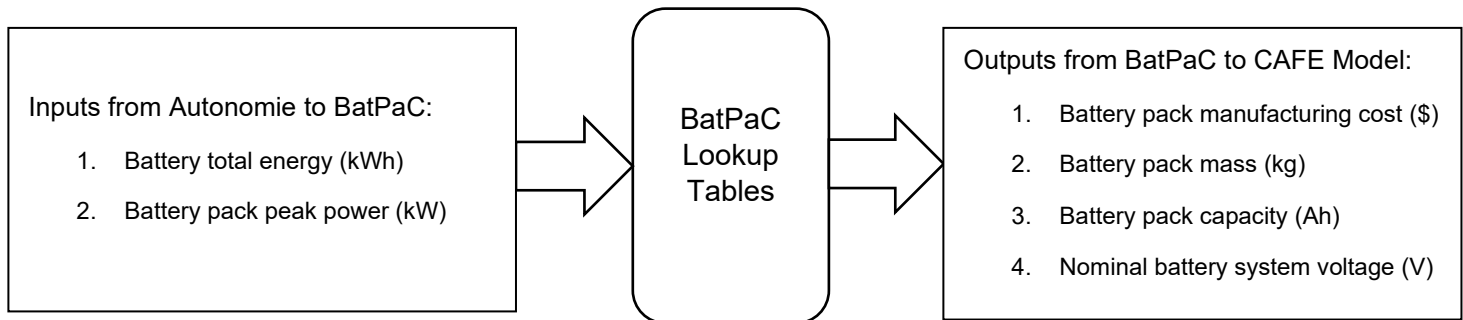
³⁷⁵ Argonne National Laboratory, BatPaC: Battery Manufacturing Cost Estimation, available at: <https://www.anl.gov/partnerships/batpac-battery-manufacturing-cost-estimation> (accessed: Apr. 3, 2026).

³⁷⁶ Knehr, K. W. *et al.*, Battery Performance and Cost Modeling for Electric-Drive Vehicles, Fourth Edition, Argonne National Laboratory, ANL/CSE-22/1 (2022), available at: <https://publications.anl.gov/anlpubs/2022/07/176234.pdf> (accessed: Apr. 3, 2026). To request the BatPaC model used in this analysis, submit the request using the instructions at: <https://www.anl.gov/partnerships/batpac-battery-manufacturing-cost-estimation>.

impractical. 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 3-16 below 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 metrics, such as cell and pack costs, pack mass, pack capacity, and pack voltage.

Figure 3-16: Flowchart Showing How Autonomie Calls BatPaC Lookup Tables



Though manufacturers’ battery pack specifications are highly heterogeneous in the real world, NHTSA endeavors 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 MY 2022 (in 2024 dollars). As detailed in the BatPaC model documentation, the costs of materials, labor, and capital equipment in the Model are based on Argonne’s estimates.³⁷⁷

NHTSA uses vehicle and battery outlook reports,^{378,379,380,381} vehicle teardown reports,^{382,383} and stakeholder discussions to determine most common battery pack chemistries for each modeled hybrid technology.³⁸⁴ In addition, NHTSA looks at vehicle sales volumes³⁸⁵ in MY 2022 to determine a reasonable base production volume assumption. The CAFE Analysis Autonomie Documentation details

³⁷⁷ *Id.*, at pp. 1 – 2.

³⁷⁸ Rho Motion (now under Benchmark Mineral Intelligence), Seminar Series Live, Q1 2023 – Seminar Recordings, Emerging Battery Technology Forum (2023). Note that this seminar video series is no longer publicly available to non-subscribers, and Rho Motion’s content has additionally moved to Benchmark Mineral Intelligence. Benchmark Source available here: <https://source.benchmarkminerals.com> (accessed: Apr. 3, 2026).

³⁷⁹ Rho Motion, EV & Battery monthly & quarterly subscriptions (2023) (proprietary data).

³⁸⁰ Benchmark Mineral Intelligence, Lithium-Ion Batteries, Cathode, & Anode monthly & quarterly subscriptions (2023) (proprietary data).

³⁸¹ International Energy Agency, Global EV Outlook 2022 – Securing Supplies for an Electric Future, International Energy Agency: Paris, France (2022), available at: <https://iea.blob.core.windows.net/assets/ad8fb04c-4f75-42fc-973a-6e54c8a4449a/GlobalElectricVehicleOutlook2022.pdf> (accessed: Apr. 3, 2026).

³⁸² Hummel, P. *et al.*, UBS Evidence Lab Electric Car Teardown – Disruption Ahead? UBS: Zurich, Switzerland (2017), available at: <https://neo.ubs.com/shared/d1ZTxnvF2k> (accessed: Apr. 3, 2026).

³⁸³ A2Mac1: Automotive Benchmarking (proprietary data), available at: <https://a2mac1.com/> (accessed: Apr. 3, 2026).

³⁸⁴ 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, available under References and Supporting Material in the rulemaking Docket No. NHTSA-2023-0022.

³⁸⁵ MY 2022 Mid-Model Year Data (see Chapter 2.2.1.1).

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.³⁸⁶ NHTSA discusses 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 of a battery pack over time, in which any future model year could be representative of the cost to manufacture a battery pack; 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’ battery packs in MY 2022 for LDVs, NHTSA works 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-level information of the vehicles in the marketplace.³⁸⁷ The CAFE Analysis Autonomie Documentation includes more detail about the reports referenced for this analysis.³⁸⁸ For the base year battery pack costs, Table 3-53 shows the battery chemistries that NHTSA assumes for each hybrid technology.

Table 3-53: Base Year Battery Chemistries Assumed by Applications

Hybrid Technology	Battery Chemistry
Mild HEV	Lithium Iron Phosphate (LFP)-G
SHEV	NMC622-G (Power Cell)
PHEV20	NMC622-G (Power Cell)
PHEV50	NMC622-G (Energy Cell)

As discussed further in Chapter 3.3.5 below, for mild HEVs, NHTSA uses the LFP-G chemistry because power and energy requirements for mild hybrid batteries are very low,³⁸⁹ 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. NHTSA currently uses NMC622-G for all other initial hybrid vehicle technology battery pack cost calculations.³⁹⁰

NHTSA accounts for the potential cost savings for *future* battery cell chemistries using a learning rate applied to the battery pack DMC. The battery chemistry NHTSA uses is intended to represent what is used in U.S. battery manufacturing in MY 2022, the DMC base year (in 2021\$) for the BatPaC calculations. Costs are updated to 2024\$ for this analysis.

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 produce varying battery pack construction designs with different cell

³⁸⁶ Chapter titled “BatPac Lookup Tables” of the CAFE Analysis Autonomie Documentation.

³⁸⁷ A2Mac1: Automotive Benchmarking (proprietary data), available at: <https://a2mac1.com/> (accessed: Apr. 3, 2026).

³⁸⁸ CAFE Analysis Autonomie Documentation, titled “Cathode/Anode Combination Selection.”

³⁸⁹ Lithium iron phosphate (LiFePO₄) cathode and graphite (G) anode.

³⁹⁰ Lithium nickel manganese cobalt oxide (LiNiMnCoO₂) cathode and graphite (G) anode.

interconnectivities (to alter overall pack power and 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 HEV 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. NHTSA examines battery pack designs for vehicles sold in MY 2022 to determine a reasonable manufacturing plant production volume assumption. NHTSA considers each assembly line and material processing designed for a specific battery pack and for a specific hybridized vehicle (such as a SHEV) as an individual battery plant. Because battery technologies are still evolving, battery cells cannot yet 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 3-54 shows the assumed base year (MY 2022) battery manufacturing plant production volume for this analysis.

Table 3-54: Battery Manufacturing Plant Production Volume Assumption for Different Hybrid Technologies for MY 2022

Technology	Production Volume
Mild HEV	200,000
SHEV	200,000
PHEVs	20,000

NHTSA uses vehicle sales as a starting point to analyze potential base modeled battery manufacturing plant production volume assumptions. Because 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,³⁹¹ NHTSA calculates an average production volume per manufacturer metric to approximate hybrid vehicle production volumes for this analysis. This metric is calculated by taking an average of all mid-model year manufacturers' battery energy across all hybrid vehicle types reported in vehicle manufacturers' pre-MY 2022 reports and dividing by the sales-weighted average energy per vehicle.³⁹² The resulting volume is then rounded to the nearest 5,000. This process is repeated for all hybrid vehicle technologies, as reflected in Table 3-54 above. Despite the absence of direct production data, NHTSA is able to correlate the known, accurate, and related mid-model year 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.³⁹³ An example calculation below, in Table 3-55, Equation 3-2, and Equation 3-3 outlines how the sales-weighted energy per-vehicle production volume estimates are calculated. Table 3-55 shows several (theoretical) example SHEV models, their production volumes, and pack energy that are representative of industry today.

³⁹¹ Zhou, Y. *et al.*, Lithium-Ion Battery Supply Chain for E-Drive Vehicles in the United States: 2010-2020, ANL/ESD-21/3, Argonne National Laboratory: Argonne, IL (2021), available at: <https://publications.anl.gov/anlpubs/2021/04/167369.pdf> (accessed: Apr. 3, 2026).

³⁹² 49 CFR 537.7 - Pre-model year and mid-model year reports.

³⁹³ NHTSA used publicly available range and pack size information and linked the information to vehicle models.

Table 3-55: Example SHEV Model Battery Packs

Hybridization Level	Vehicle Make	Vehicle Model	Production Volume	Battery Pack Energy
SHEV	Make A	Model A1	98,000	1.3kWh
SHEV	Make A	Model A2	181,000	1.1kWh
SHEV	Make B	Model B1	12,000	1.9kWh
SHEV	Make C	Model C1	15,000	1.1kWh

The average energy (E_{avg}) across all vehicles for a level of hybridization in the fleet is initially found. In this SHEV example, the average energy is calculated as the sum of the pack energy divided by the number of vehicle models:

Equation 3-1: Example Average SHEV Energy Calculation

$$E_{avg} = \frac{E_{Model A1} + E_{Model A2} + E_{Model B1} + E_{Model C1}}{N_{Vehicle\ models}} = \frac{1.3kWh + 1.1kWh + 1.9kWh + 1.1kWh}{4} = 1.35kWh \text{ average energy (theoretical example)}$$

Next, the average production volume (P_{avg}) is 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 3-2: Example SHEV Sales-Weighted Average Production Volume

$$P_{avg} = \frac{(E_{Model A1} * P_{Model A1}) + (E_{Model A2} * P_{Model A2}) + (E_{Model B1} * P_{Model B1}) + (E_{Model C1} * P_{Model C1})}{E_{avg}} = \frac{(1.3kWh * 98,000) + (1.1kWh * 181,000) + (1.9kWh * 12,000) + (1.1kWh * 15,000)}{1.35kWh} = 270,962.96 \approx 270,000 \text{ average SHEV production (THEORETICAL EXAMPLE ONLY)}$$

Once the average SHEV production (P_{avg}) is found, it is rounded to the nearest 5,000. For this theoretical example, the production volume is rounded from 270,962.96 to 270,000 vehicles. This process is used to determine production volumes for each of the hybrid technologies in the fleet. The battery manufacturing plant production volume assumptions for different hybrid technologies are shown above in Table 3-55.

Manufacturers design vehicles to suit local or regional duty cycles due to local geography and climate, customer preferences, affordability, and supply constraints. Vehicles sold in the United States have different performance metrics and battery technology compared to the same vehicle sold in other parts of the world.³⁹⁴ NHTSA considers United States sales—not global sales—when estimating battery pack production volume. NHTSA believes it is reasonable to consider U.S. sales for purposes of this

³⁹⁴ Rho Motion, EV Battery monthly assessment, Figure: YTD weighted average PHEV and combined pack size by region, PC & light-duty vehicle (2023) (proprietary data).

calculation, rather than global sales, based on the best available data at the time of modeling and based on the agency’s understanding of how manufacturers design vehicles for particular markets. However, manufacturers may take advantage of design overlaps 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. As the outlook for battery materials and global economic events 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. To the extent that manufacturers’ costs are based more closely on global volumes of battery packs produced, the base year battery pack production volume assumption could potentially be conservative; however, the base year MY 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 3-56 and Table 3-57 show SHEV base MY 2022 battery pack costs in 2021\$³⁹⁵ for all vehicle technology classes. These tables demonstrate how the cost per kW / kWh varies with the size of the battery pack. Though the overall cost of a battery pack increases for higher power/energy battery packs, the cost per kW/kWh decreases. This represents the cost of hardware needed in all battery packs but is spread across more kW/kWh in larger packs, thus reducing the per kW/kWh cost.

The full range of BatPaC-generated battery DMCs are located in ANL - Summary of Main Component Performance Assumptions_NPRM_2206. These charts represent the direct manufacturing cost using a dollar per kW/kWh metric; battery absolute costs used in the analysis by technology key are located in the CAFE Model Battery Costs File.

Table 3-56: \$/kWh Battery Packs Costs – Compact Through Mid-size SHEV

\$/kWh at Pack Level (Total Energy) for Compact Through Mid-size Vehicle Technology Class																
SHEV		Energy, kWh														
		0.30	0.50	0.70	0.90	1.0	1.2	1.4	1.6	1.8	2.0	2.2	2.4	2.6	2.8	3.0
Power, kW	10.0	49	51	53	55	56	58	61	63	65	67	69	71	73	76	78
	20.0		26	27	28	29	30	31	31	33	34	35	36	37	38	39
	30.0			19	19	20	20	21	22	22	23	23	24	25	25	26
	40.0			15	15	15	16	16	17	17	17	18	18	19	19	20
	60.0							11	12	12	12	13	13	13	13	14
	80.0									9	10	10	10	10	10	11
	100.0											8	8	9	9	9

Table 3-57: \$/kWh Battery Packs Costs – SUV Through Pickup SHEV

\$/kWh at Pack Level (Total Energy) for SUV Through Pickup Vehicle Technology Class																
SHEV		Energy, kWh														
		0.9	1.0	1.2	1.4	1.6	1.8	2.0	2.2	2.4	2.6	2.8	3.0	3.4	3.8	4.0
Power, kW	10.0	65	66	69	71	73	75	78	80	82	84	86	88	93	97	99
	20.0	33	34	35	36	37	38	39	40	41	42	43	44	46	48	49

³⁹⁵ Costs for this analysis are converted to 2024\$.

	30.0	23	23	24	24	25	26	26	27	27	28	29	30	31	32	33
	40.0	18	18	18	19	19	20	20	21	21	21	22	22	23	24	25
	60.0			13	13	13	14	14	14	15	15	15	15	16	17	17
	80.0				10	10	11	11	11	11	12	12	12	12	13	13
	100.0						9	9	9	9	10	10	10	10	11	11
	150.0											7	7	7	8	8
	200.0														6	6

3.3.5.2. Non-Battery Hybrid Component Costs

Though batteries and relative battery components are a large cost driver of vehicle hybridization, non-battery hybrid components, such as electric motors, power electronics, thermal management systems, and wiring harnesses, also add to the total cost required to hybridize a vehicle. Different hybrid vehicles have variations of non-battery hybrid components and configurations to accommodate different vehicle classes and applications with respective designs. In addition, some hybrid vehicle types still include conventional components, like an ICE and traditional transmission. Chapter 3.3.5.3 discusses how the battery costs, non-battery hybridization component costs, and other conventional technology costs come together to create a total vehicle cost for various levels of hybrid vehicles.

For all other hybrid vehicle powertrain types, NHTSA groups non-battery hybrid components into four major categories: electric motors/generators, power electronics (generally including the DC/DC converter, inverter, and power distribution module), charging components (charging unit, charging cable, and high voltage cables), and thermal management system(s).

NHTSA further groups the components into those comprising the ETDS and all other components. Though each manufacturer's ETDS and power electronics vary between the same hybrid vehicle types and between different hybrid vehicle types and architectures, NHTSA considers the ETDS for this analysis to comprise the electric motor and inverter, power electronics, and thermal management system. Table 3-58 shows the assignments for each of the non-battery hybrid components to in the analysis.

Table 3-58: Non-Battery Hybrid Component and Vehicle Assignment

Major Non-Battery Hybrid Components	HEV*	PHEV
Electric Motor	X	X
Electric Generator**	X	X
Power Electronics	X	X
DC/DC Converter	X	X
Charging Port and High Voltage cable	N/A	X
On-board Charger	N/A	X
Thermal Management System	X	X

When researching costs for different non-battery hybrid components, NHTSA found that different reports vary in the cost breakdown and the components under consideration due to variations in vehicle classes, applications, and corresponding designs. This is not surprising, as vehicle manufacturers use different

non-battery hybrid components in different vehicles systems, or even in the same vehicle type, depending on the application. NHTSA applies costs for the major non-battery hybrid vehicle 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 report³⁹⁶—one of the sources NHTSA uses for non-battery hybrid component costs. This approach captures components in most, but not all, manufacturers’ systems. NHTSA believes that this is a reasonable metric and approach for this analysis, given the non-standardization of hybridized powertrain designs and subsequent component specifications.

NHTSA adjusts 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 2024\$ for this analysis.

3.3.5.2.1. *Micro Hybrid and Mild Hybrid Costs*

Beginning with the least complex hybrid systems, the SS12V micro hybrid system cost in this analysis is based on a single small electric motor and battery. The electric motor is a fixed cost regardless of the engine type with which the system is paired (*e.g.*, turbocharged or naturally aspirated), but the cost varies by vehicle class. NHTSA uses motor costs from the 2016 Draft TAR and updates the cost to 2024\$.³⁹⁷ The DMC for the SS12V motor is \$195.00 for the small car, medium car, and small SUV vehicle classes and \$260.42 for the medium SUV and LD pickup classes.

Like the SS12V system, the 48V BISG mild hybrid non-battery hybrid component costs are fixed for all technology classes. NHTSA uses the A2Mac1 database to develop a bill of materials for the BISG system and cost the components using two sources, as explained below. Table 3-59 lists the non-battery hybrid components that comprise the mild hybrid system and the cost of those components in the analysis.

³⁹⁶ DOE, Electrical and Electronics Technical Team Roadmap, DOE: Washington, D.C., (2017), available at: <https://www.energy.gov/eere/vehicles/articles/us-drive-electrical-and-electronics-technical-team-roadmap> (accessed: Apr. 3, 2026).

³⁹⁷ Draft TAR, at p. 5 – 453.

Table 3-59: Cost Estimate of BISG Components in 2024\$

Components	DMC	RPE
Motor, inverter, and cooling system (10kW)	225	337
DC/DC converter (2kW)	225	337
Water pump	53	79
Wiring harness	35	53
Connecters	12	18
Belt pulley modifications to Air Conditioning compressor	12	18
Auxiliary electric oil pump to transmission	56	84
Modifications to auxiliary brake pump	53	79
Brackets for motor and battery attachment	18	28
Total non-battery component cost	690	1,034

NHTSA uses 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.³⁹⁸ For all other BISG component costs shown in Table 3-59, NHTSA relies on an EPA-sponsored FEV teardown of a 2013 Chevrolet Malibu ECO with eAssist.³⁹⁹ FEV estimates the direct manufacturing cost of the BISG system (without batteries) to be \$1,045 in 2013 dollars, which is equivalent to \$1,385.28 in 2024 dollars—this includes a cost adjustment for reduced voltage insulation. Even though the 2013 Chevrolet Malibu considered in the study used a 115V system, NHTSA determines that structural components, like the motor and battery attachment brackets, translate fairly across BISG systems regardless of system voltage.

To validate these costs, NHTSA considers the 2019 Dodge Ram eTorque system retail price. Using the publicly available retail price,⁴⁰⁰ NHTSA estimates 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 2025.⁴⁰¹ This is equivalent to a range of \$1,245.51 to \$1,632.64 in 2024 dollars in 2025. Broadly, the total BISG system cost, including the battery, conservatively matches these estimates.

³⁹⁸ DOE, Electrical and Electronics Technical Team Roadmap, DOE: Washington, D.C., (2017), available at: <https://www.energy.gov/eere/vehicles/articles/us-drive-electrical-and-electronics-technical-team-roadmap> (accessed: Apr. 3, 2026).

³⁹⁹ FEV, Inc., 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, EPA: Washington, D.C., (2014), available at: <https://www.regulations.gov/document/EPA-HQ-OAR-2015-0827-0342> (accessed: Apr. 3, 2026).

⁴⁰⁰ Colwell, K.C., The 2019 Ram 1500 eTorque Brings Some Hybrid Tech, If Little Performance Gain, to Pickups, last revised: Mar. 14, 2019, available at: <https://www.caranddriver.com/reviews/a22815325/2019-ram-1500-etorque-hybrid-pickup-drive> (accessed: Apr. 3, 2026).

⁴⁰¹ 2015 NAS report, at p. 305.

3.3.5.2.2. Strong Hybrid and Plug-in Hybrid Vehicle Costs

To estimate the cost of the ETDS, NHTSA uses 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 \$22.51/kW in 2024\$.

The EETT Roadmap report does 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. NHTSA relies on the UBS teardown report to estimate those individual costs for some categories of strong hybrid components and all other PHEV components.

The strong hybrid high-voltage cable costs are from the EPA-sponsored 2011 Ford Fusion HEV teardown study.⁴⁰² NHTSA adjusts the costs for high voltage cables from the 2011 Ford Fusion HEV teardown study to 2024\$ and applies that to both PS and P2 strong hybrid cables.

Table 3-60 shows the cost estimates for the ETDS from the EETT Roadmap report, the UBS teardown report, and the EPA-sponsored FEV report (with updated 2024\$ costs).

Table 3-60: Cost Estimates from the EETT Roadmap Report, UBS Teardown, and FEV 2011 Ford Fusion HEV Teardown

Non-Battery Electrical Components	EETT Roadmap Report (2017\$ in DMC Year 2017)	UBS Teardown (2017\$ in DMC Year 2017)	Assumptions	EPA-Sponsored FEV Report (Updated 2024\$ for Analysis)
ETDS	\$18/kW	\$17.76/kW	Based on e-motor peak power	\$22.51/kW
On-Board Charger	no information provided	\$85/kW	Based on vehicle requirement (7 kW for BEVs, 2 kW for PHEVs)	\$106.32/kW
DC/DC Converter	no information provided	\$90/kW	Based on converter rated power (2 kW)	\$114.74/kW
High Voltage Cables and Charging Cords for PHEVs	no information provided	\$450	Fixed cost rated for 360V	\$562.89
High Voltage Cables for Strong Hybrids	no information provided	no information provided	Fixed cost	\$114.17

⁴⁰² FEV Inc., Light Duty Technology Cost Analysis, Power-Split and P2 HEV Case Studies, Technical Report, EPA-420-R-11-015, Assessment and Standards division, Washington, D.C.: EPA (2011), available at: <https://nepis.epa.gov/Exe/ZyPDF.cgi/P100EG1R.PDF?Dockey=P100EG1R.PDF> (accessed: Apr. 3, 2026).

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, Argonne develops battery cost correlation equations from BatPaC for use in the CAFE Model.⁴⁰³ These cost equations—for use through MY 2035—are tailored for different vehicle segments,⁴⁰⁴ different levels of powertrains,⁴⁰⁵ and anticipated plant production volumes.⁴⁰⁶ These equations represent cost improvements achieved from advanced manufacturing, pack design, and cell design with current and anticipated future battery chemistries,⁴⁰⁷ design parameters, forecasted market prices, and vehicle technology market penetration.

The battery cost correlation Equation 3-3^{408,409} below uses different coefficients (see Table 3-61) for HEVs⁴¹⁰ compared to the coefficients used for PHEVs; note that for PHEVs, the coefficients differ for Ni/Mn (NMC) and LFP cathode chemistries.

Equation 3-3: Battery Pack Cost Correlation Equation

$$C_{pack} = A + \frac{B}{x^C} - D(y - 2023)e^{E(y - 2023)}$$

Table 3-61: Correlation Equation Coefficients

Coefficient	HEV (≤ 5kWh)	PHEV	
	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

The remaining correlation equation variables x and y correspond to pack energy (kWh) and model year, respectively, and these inputs are ultimately used to develop learning curves for each vehicle class and level of hybrid technology for the analysis.

⁴⁰³ Argonne National Laboratory, Cost Analysis and Projections for U.S.-Manufactured Automotive Lithium-Ion Batteries, ANL/CSE-24/1, ANL (2024), available at: <https://publications.anl.gov/anlpubs/2024/01/187177.pdf> (accessed: Apr. 29, 2026).

⁴⁰⁴ The vehicle classes considered in this project include compact cars, mid-size cars, mid-size SUVs, and pickup trucks.

⁴⁰⁵ The powertrains considered in this project that were used in this analysis include light-duty HEVs and PHEVs.

⁴⁰⁶ Production volumes were determined for each vehicle class and type for each model year. See Equation 1 and Table 13 of Argonne National Laboratory, Cost Analysis and Projections for U.S.-Manufactured Automotive Lithium-ion Batteries, ANL/CSE-24/1, ANL (2024), available at: <https://publications.anl.gov/anlpubs/2024/01/187177.pdf> (accessed: Apr. 6, 2026).

⁴⁰⁷ 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.

⁴⁰⁸ C_{pack} unit of measurement is in \$/kWh.

⁴⁰⁹ The coefficients used assume a \$50/hour labor rate.

⁴¹⁰ ≤ 5kWh battery, Ni/Mn cathode.

Autonomie full-vehicle model simulation data⁴¹¹ is used to determine average battery pack energy across vehicle segments (variable x). Table 3-62 below presents the corresponding average pack energy values used as inputs to the battery cost correlation equations.

⁴¹¹ For details of how Autonomie full-vehicle simulations were used for this rulemaking see Chapter 2.4.

Table 3-62: Average Battery Pack Energy Values from Autonomie Full-Vehicle Model Simulations Across Vehicle Segments and Hybrid Technologies

Average Pack Energy (kWh)	SmallCar	SmallCarPerf	MedCar	MedCarPerf	SmallSUV	SmallSUVPerf	MedSUV	MedSUVPerf	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

In addition, due to the increasing prevalence of LFP displacing NMC cathodes in the U.S. PHEV market, NHTSA uses a dynamic NMC/LFP mix between the battery cost correlation equations, referred to as a composite correlation equation; LFP market projections⁴¹² used for the mix are noted below in Table 3-63. For the model years that the composite cost equation covers (for model years through MY 2035), NHTSA assumes the NMC battery cathode chemistry for the remaining market share. The composite cost equation only corresponds with PHEV technologies and not lower levels of HEV technologies.

Table 3-63: U.S. Market Share Cathode Projections for 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 hybrid technologies through MY 2035. NHTSA uses a learning plateau cost constant in place of the battery cost correlations

⁴¹² A composite learning curve (used for PHEV 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.

between MYs 2022-2025 to reflect the combination of increasing mineral costs, changing demand, and uncertainty in manufacturers' ability to increase production in such short timeframe.^{413,414}

Beyond the extent of the battery cost correlation equation, starting in MY 2036, a constant 1.5-percent learning rate⁴¹⁵ is used through MY 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.

In combination with the base year (MY 2022) DMC battery costs⁴¹⁶ and an RPE factor, the resulting battery learning curves are calculated and embedded in the Technologies Input File for use in the analysis. Chapter 3.3.5.1.3 contains more information on the base year battery pack DMCs. Chapter 2.1.3 and Chapter 2.1.9 include more information on the Technologies Input File.

The agencies determine this battery learning approach is a reasonable method for representing manufacturing technologies that are rapidly advancing.

3.3.5.3.2. *Non-Battery Hybridization Learning Curves*

For the non-battery hybrid component learning curves, NHTSA uses cost information from Argonne's 2016 Assessment of Vehicle Sizing, Energy Consumption, and Cost through Large-Scale Simulation of Advanced Vehicle Technologies report.⁴¹⁷ The report provides estimated cost projections from the 2010 lab year to the 2045 lab year for individual vehicle components.^{418,419} NHTSA considers the component costs used in hybrid vehicles and determined the learning curve by evaluating the year over year cost change for those components. In addition, Argonne published a 2020 and a 2022 version of the same report; however, those versions did not include a discussion of the high- and low-cost estimates for the same components.^{420,421} The learning estimates—generated using the 2016 report—align in the middle of these two ranges, and NHTSA continues to apply the learning curve estimates based on the 2016 report. There are many sources that NHTSA could have picked to develop learning curves for non-battery hybrid component costs; however, given the uncertainty surrounding extrapolating costs out to MY 2050, NHTSA believes these learning curves provide a reasonable estimate.

⁴¹³ U.S. Geological Survey, Lithium Statistics and Information, available at: <https://www.usgs.gov/centers/national-minerals-information-center/lithium-statistics-and-information> (accessed: Apr. 6, 2026).

⁴¹⁴ Barlock, T.A. *et al.*, Securing Critical Materials for the U.S. Electric Vehicle Industry: A Landscape Assessment of Domestic and International Supply Chains for Five Key Battery Materials, ANL-24/06, Final Report, ANL: Washington, D.C. (2024), available at: <https://publications.anl.gov/anlpubs/2024/03/187907.pdf> (accessed: Apr. 6, 2026).

⁴¹⁵ NHTSA uses the 1.5-percent learning rate from MY 2036 onward for the final rule.

⁴¹⁶ Battery costs are unique across vehicle types and across powertrain technologies. Base battery costs can be found in the CAFE Model Battery Costs File.

⁴¹⁷ Moawad, A. *et al.*, Assessment of Vehicle Sizing, Energy Consumption and Cost Through Large-Scale Simulation of Advanced Vehicle Technologies, ANL/ESD-15/28, ANL: Washington, D.C., (2016), available at: <https://publications.anl.gov/anlpubs/2016/04/126422.pdf> (accessed: Apr. 6, 2026) (hereinafter, "ANL/ESD-15/28").

⁴¹⁸ ANL/ESD-15/28, at p. 116.

⁴¹⁹ DOE's lab year equates to 5 years after a model year (*e.g.*, DOE's 2010 lab year equates to MY 2015).

⁴²⁰ Islam, E. S. *et al.*, 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, ANL: Washington, D.C., (2020), available at: <https://publications.anl.gov/anlpubs/2020/08/161542.pdf> (accessed: Apr. 6, 2026).

⁴²¹ Islam, E. S. *et al.*, A Detailed Vehicle Modeling & Simulation Study Quantifying Energy Consumption and Cost Reduction of Advanced Vehicle Technologies Through 2050 Department of Energy, ANL/ESD-21/10, ANL: Washington, D.C., (2021), available at: <https://doi.org/10.2172/1866349> (accessed: Apr. 6, 2026).

Table 3-63 and Table 3-64 show the learning rate factors for non-battery hybrid components for different hybrid powertrains.

Table 3-64: Learning Rate Factor Used for Non-Battery Hybrid Components for Hybridized Powertrains (MYs 2017-2031)

Technology	Model Year											
	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031
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
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
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
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

3.3.5.4. Total Hybrid Powertrain Costs

NHTSA calculates total hybrid powertrain costs by summing individual component costs, which ensures that all technologies in a hybrid powertrain appropriately contribute to the total system cost. NHTSA combines the costs associated with the ICE and transmission, non-battery hybrid components like the electric machine, and battery pack to create a full-system cost. The following subchapters describe how NHTSA calculates the aggregated cost of each hybrid powertrain based on the detailed component costs presented in the earlier subchapters.

The application of the hybridization costs to an existing platform follows the same basic process for each technology on the hybridization path. The costs for each technology depend on the model year to which 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 hybridization technology.

The incremental costs for these hybrid 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 3-65 shows a summary of the general components considered for each hybrid technology and where the costs of those components can be found in the CAFE Model Input File folders.

Table 3-65: Breakdown of the Component Costs Considered in the CAFE Analysis

Hybrid Technology Type	Technologies Input File; Vehicle Tabs	Technologies Input File; Engine Tabs	CAFE Model Battery Costs File ⁴²²
Micro Hybrid (SS12V)	Motor/generator	N/A	Battery pack ⁴²³
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	ICE*	Battery pack
Strong Hybrid with Power-Split Device (SHEVPS)	DC/DC converter, high-voltage cables, motor/generator, eCVT transmission, and power electronics	ICE	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	ICE	Battery pack
Plug-in Hybrid with Parallel Architecture and HCR Engine (20H/50H)	DC/DC converter, on-board charger, high-voltage cables, motor/generator,	ICE	Battery pack

⁴²² The CAFE Model Battery Costs File is installed as part of the CAFE Model installation and is viewable in the CAFE Model Program Directory.

⁴²³ As discussed further in this chapter, NHTSA no longer uses 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.

	AT8L2 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	ICE	Battery pack

*The engine cost for a P2 Hybrid is based on engine technology used in the CONV.

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 reflects the cost of the absorbed-glass-mat (AGM) battery chemistry. The battery pack DMC for SS12V systems is \$117.31⁴²⁴ across all vehicle classes, as shown in Table 3-66 below. This cost more closely aligns with the cost of the SS12V system presented in the 2015 NAS report.⁴²⁵

Unlike the rest of the hybrid 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 NHTSA discusses in Chapter 3.3.2, approximately 60 percent of the MY 2024 fleet utilizes a SS12V micro hybrid system.⁴²⁶

Table 3-66 lists the cost of the SS12V system and battery for different vehicle classes. For the SS12V hybrid, the Technologies Input File contains the cost of the non-battery components with RPE and learning, as well as the learning factor for the battery for each vehicle class.

Table 3-66: MY 2024 SS12V Total Cost for All Vehicle Classes in 2024\$

	Small Car	Medium Car	Small SUV	Medium SUV	Pickup
Non-battery Component DMC	\$154.46	\$154.46	\$154.46	\$206.29	\$206.29
Non-battery Component Cost with RPE	\$231.69	\$231.69	\$231.69	\$309.44	\$309.44
Battery Pack DMC	\$117.31	\$117.31	\$117.31	\$117.31	\$117.31
Battery Pack Cost with RPE	\$175.97	\$175.97	\$175.97	\$175.97	\$175.97
Total System Cost	\$407.65	\$407.65	\$407.65	\$485.44	\$485.44

⁴²⁴ This cost reflects an update to 2024\$ from 2021\$, as base year battery costs in the CAFE Model Battery Costs File are in 2021\$ (for MY 2022); this specific value also includes learning.

⁴²⁵ 2015 NAS report, at p. 158.

⁴²⁶ SS12V technology penetration in the analysis fleet is 62.97 percent.

3.3.5.4.2. Mild Hybrid Cost

NHTSA uses 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 battery 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 the battery cost. The Technologies Input File includes the battery learning rate, while the CAFE Model Battery Costs File provides only the battery DMC for MY 2022 (in 2021\$). Costs for this analysis are converted to 2024\$ with both learning⁴²⁷ and a GDP inflator adjustment factor.⁴²⁸ To determine the total cost of the system for a vehicle of a particular year, the vehicle technology class's technology key must align between the two files.

Table 3-67 below shows how costs are added to create the total BISG system cost. As an example, the MY 2024 medium car BISG non-battery component cost of \$657.01 can be found on the 'MedCar' tab in the Technologies Input File.⁴²⁹ This cost includes a learning rate specific to the non-battery components as well as RPE. The medium car BISG battery cost can be found in the CAFE Model Battery Costs File in \$294.46 in 2021\$; this base DMC is then multiplied by 1.4436⁴³⁰ from the Battery Cost Learning Rates Table (columns 'AV' and onward on the 'MedCar' tab). With the additional GDP inflator adjustment from 2021\$ to 2024\$, this results in a battery cost of \$483.18.

These two costs (battery and non-battery), which are both for MY 2024, sum to \$1,140.19 for the total cost.

Table 3-67: Example of MY 2024 Mild Hybrid Total Cost for Different Vehicle Classes in 2024\$

	Small Car	Medium Car	Small SUV	Medium SUV	Pickup
Non-battery Component DMC	\$438.01	\$438.01	\$438.01	\$438.01	\$438.01
Non-battery Component Cost with RPE	\$657.01	\$657.01	\$657.01	\$657.01	\$657.01
Battery Pack DMC	\$322.12	\$322.12	\$322.12	\$322.12	\$322.12
Battery Pack Cost with RPE	\$483.18	\$483.18	\$483.18	\$483.18	\$483.18
Total System Cost	\$1,140.19	\$1,140.19	\$1,140.19	\$1,140.19	\$1,140.19

3.3.5.4.3. Strong Hybrid and Plug-in Hybrid Vehicle Costs

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.

⁴²⁷ To extract the learning rate without RPE included, divide the learning value (for the appropriate year) found in the Technologies Input File by 1.50.

⁴²⁸ Consistent with other adjustments made throughout the analysis from 2021\$ to 2024\$, a factor of 1.137 was used.

⁴²⁹ Note that regardless of vehicle type, the BISG cost is the same in this analysis.

⁴³⁰ This value from the learning table is the product of 1.5 RPE and a learning factor of 0.9624 because the base learning rate year for batteries is 2021.

SHEVP2 and SHEVPS have different architectures and powertrain characteristics and have different costs. NHTSA bases the cost of SHEVP2 engines and transmissions on estimates discussed 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 and in detail in the CAFE Analysis Autonomie Documentation.⁴³¹ SHEVPS total powertrain costs include the optimized battery pack, electric machines, Atkinson engine, and eCVT. Like SHEVP2, the costs of the SHEVPS electric machines and battery pack 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 includes the cost of the motor/generators (electric traction motor, electric generator motor), power electronics (power inverter and DC/DC converter), high voltage cables and connectors; for PHEVs additional costs are included for the charging cord and on-board chargers. NHTSA uses 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 coupled to the hybrid system.

Because 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. NHTSA uses 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, NHTSA multiplies the motor size by the unit cost (\$/kW) to get the overall DMC for both motor/generators, as explained in Chapter 3.3.5.2. The costs shown in the following tables are in 2024\$.

NHTSA calculates the cost of plug-in hybrid vehicles like strong hybrids by using Autonomie to optimize plug-in-hybrid system components, as explained in Chapter 3.3.4. NHTSA uses one engine technology and one transmission technology per plug-in hybrid architecture type. NHTSA uses 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 architecture path, as shown in Chapter 3.3.1, NHTSA bases the total costs on a PHEV system paired with a TURBO1 engine. NHTSA calculates the total cost for the powertrain by summing the costs of the TURBO1 engine, an AT8L2 transmission, and the battery and non-battery hybrid technology components. For PHEVs that follow the SHEVP2 architecture but adopt an HCR engine instead, NHTSA calculates the total cost of the powertrain by summing the costs of HCR engine, an AT8L2 transmission, and the battery and non-battery hybrid technology components. NHTSA calculates the total cost for PHEVs that follow the SHEVPS architecture in the hybrid architecture path by summing the costs of the Atkinson engine, the CVTL2 transmission, and the sized battery pack and non-battery hybrid technology components.

Table 3-68 and Table 3-69 below show the overall cost of hybridized powertrains for SHEVs and PHEVs. Note that the battery cost is not broken out in a separate column in this table; however, the total hybridization cost includes the cost of the battery. The total DMC of non-battery hybrid components includes the costs of motor/generator(s) (as applicable), DC/DC converter, cables, and on-board charger (for PHEV only). Chapter 3.3.5.2 contains more details of these costs.

⁴³¹ Chapter titled “Split HEV Sizing Algorithm” of the CAFE Analysis Autonomie Documentation.

Table 3-68: Cost Estimation for Hybrid and Plug-in Hybrid Electric Drivetrains for the Medium Car and Small SUV Non-Performance Vehicle Technology Classes in MY 2024 (in 2024\$)⁴³²

Electric Powertrain	Traction Motor (Peak Power) [kW]	Traction Motor DMC	Motor Generator (Continuous Power) [kW]	Motor Generator DMC	ETDS (Motor and Inverter) DMC	DC/DC Converter [kW]	DC/DC Converter	Onboard Charger [kW]	Onboard Charger	Power Distribution Cables	Electrical Component DMC	Electrical Component Total Costs	Transmission Total Costs	Non-Battery Hybrid Total Costs
Medium Car – Non-Performance														
Par HEV Turbo0 (P2TRB0)	28.24	\$637	0	\$0	\$637	2	\$230	0	\$0	\$205	\$1,072	\$1,262	\$2,949	\$4,211
Split HEV (SHEVPS)	85.19	\$1,920	44.27	\$998	\$2,918	2	\$230	0	\$0	\$205	\$3,353	\$3,948	\$1,970	\$5,918
Par PHEV20T (PHEV20T)	90.72	\$2,045	0	\$0	\$2,045	2	\$230	2	\$213	\$564	\$3,051	\$3,470	\$2,949	\$6,419
Par PHEV50T (PHEV50T)	95.83	\$2,160	0	\$0	\$2,160	2	\$230	2	\$213	\$564	\$3,166	\$3,601	\$2,949	\$6,550
Par PHEV20H (PHEV20H)	90.72	\$2,045	0	\$0	\$2,045	2	\$230	2	\$213	\$564	\$3,051	\$3,470	\$2,949	\$6,419
Par PHEV50H (PHEV50H)	95.83	\$2,160	0	\$0	\$2,160	2	\$230	2	\$213	\$564	\$3,166	\$3,601	\$2,949	\$6,550
Split PHEV20 (PHEV20PS)	97.03	\$2,187	45.78	\$1,032	\$3,219	2	\$230	2	\$213	\$564	\$4,225	\$4,806	\$3,112	\$7,918
Split PHEV50 (PHEV50PS)	116.87	\$2,634	50.93	\$1,148	\$3,782	2	\$230	2	\$213	\$564	\$4,788	\$5,446	\$3,112	\$8,558
Small SUV – Non-Performance														
Par HEV Turbo0 (P2TRB0)	28.36	\$639	0	\$0	\$639	2	\$230	0	\$0	\$205	\$1,074	\$1,265	\$2,949	\$4,214
Split HEV (SHEVPS)	93.14	\$2,099	47.30	\$1,066	\$3,165	2	\$230	0	\$0	\$205	\$3,601	\$4,239	\$1,970	\$6,210

⁴³² Numbers in this table are rounded.

Par PHEV20T (PHEV20T)	97.95	\$2,208	0	\$0	\$2,208	2	\$230	2	\$213	\$564	\$3,214	\$3,655	\$2,949	\$6,605
Par PHEV50T (PHEV50T)	103.46	\$2,332	0	\$0	\$2,332	2	\$230	2	\$213	\$564	\$3,338	\$3,797	\$2,949	\$6,746
Par PHEV20H (PHEV20H)	97.95	\$2,208	0	\$0	\$2,208	2	\$230	2	\$213	\$564	\$3,214	\$3,655	\$2,949	\$6,605
Par PHEV50H (PHEV50H)	103.46	\$2,332	0	\$0	\$2,332	2	\$230	2	\$213	\$564	\$3,338	\$3,797	\$2,949	\$6,746
Split PHEV20 (PHEV20PS)	104.63	\$2,358	48.95	\$1,103	\$3,461	2	\$230	2	\$213	\$564	\$4,468	\$5,081	\$3,112	\$8,194
Split PHEV50 (PHEV50PS)	123.47	\$2,783	54.11	\$1,220	\$4,003	2	\$230	2	\$213	\$564	\$5,009	\$5,697	\$3,112	\$8,809

Table 3-69: Cost Estimation for Hybrid and Plug-in Hybrid Electric Drivetrains for the Medium Car and Small SUV Performance Vehicle Technology Classes in MY 2024 (in 2024\$)⁴³³

Electric Powertrain	Traction Motor (Peak Power) [kW]	Traction Motor DMC	Motor Generator (Continuous Power) [kW]	Motor Generator DMC	ETDS (Motor and Inverter) DMC	DC/DC Converter [kW]	DC/DC Converter	Onboard Charger [kW]	Onboard Charger	Power Distribution Cables	Electrical Component DMC	Electrical Component Total Costs	Transmission Total Costs	Non-Battery Hybrid Total Costs
Medium Car – Performance														
Par HEV Turbo0 (P2TRB0)	29.83	\$672	0	\$0	\$672	2	\$230	0	\$0	\$205	\$1,108	\$1,304	\$2,949	\$4,253
Split HEV (SHEVPS)	118.85	\$2,679	61.39	\$1,384	\$4,063	2	\$230	0	\$0	\$205	\$4,497	\$5,295	\$1,970	\$7,266
Par PHEV20T (PHEV20T)	94.98	\$2,141	0	\$0	\$2,141	2	\$230	2	\$213	\$564	\$3,147	\$3,579	\$2,949	\$6,529
Par PHEV50T (PHEV50T)	99.91	\$2,252	0	\$0	\$2,252	2	\$230	2	\$213	\$564	\$3,258	\$3,706	\$2,949	\$6,655

⁴³³ Numbers in this table are rounded.

Par PHEV20H (PHEV20H)	94.98	\$2,141	0	\$0	\$2,141	2	\$230	2	\$213	\$564	\$3,147	\$3,579	\$2,949	\$6,529
Par PHEV50H (PHEV50H)	99.91	\$2,252	0	\$0	\$2,252	2	\$230	2	\$213	\$564	\$3,258	\$3,706	\$2,949	\$6,655
Split PHEV20 (PHEV20PS)	119.49	\$2,693	63.37	\$1,428	\$4,121	2	\$230	2	\$213	\$564	\$5,128	\$5,832	\$3,112	\$8,944
Split PHEV50 (PHEV50PS)	168.48	\$3,797	69.86	\$1,574	\$5,371	2	\$230	2	\$213	\$564	\$6,378	\$7,254	\$3,112	\$10,366
Small SUV – Performance														
Par HEV Turbo0 (P2TRB0)	30.39	\$685	0	\$0	\$685	2	\$230	0	\$0	\$205	\$1,120	\$1,319	\$2,949	\$4,268
Split HEV (SHEVPS)	114.92	\$2,590	56.9	\$1,283	\$3,873	2	\$230	0	\$0	\$205	\$4,308	\$5,072	\$1,970	\$7,042
Par PHEV20T (PHEV20T)	102.87	\$2,319	0	\$0	\$2,319	2	\$230	2	\$213	\$564	\$3,325	\$3,782	\$2,949	\$6,731
Par PHEV50T (PHEV50T)	108.27	\$2,440	0	\$0	\$2,440	2	\$230	2	\$213	\$564	\$3,447	\$3,920	\$2,949	\$6,869
Par PHEV20H (PHEV20H)	102.87	\$2,319	0	\$0	\$2,319	2	\$230	2	\$213	\$564	\$3,325	\$3,782	\$2,949	\$6,731
Par PHEV50H (PHEV50H)	108.27	\$2,440	0	\$0	\$2,440	2	\$230	2	\$213	\$564	\$3,447	\$3,920	\$2,949	\$6,869
Split PHEV20 (PHEV20PS)	118.22	\$2,665	58.84	\$1,326	\$3,991	2	\$230	2	\$213	\$564	\$4,997	\$5,683	\$3,112	\$8,796
Split PHEV50 (PHEV50PS)	149.48	\$3,369	64.45	\$1,453	\$4,821	2	\$230	2	\$213	\$564	\$5,828	\$6,628	\$3,112	\$9,740

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 mass reduction 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 promote mass reduction (advanced high strength steel (AHSS), aluminum, magnesium, and plastics, including carbon fiber reinforced plastic (CFRP)).

The cost for mass reduction 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 equipment. In addition, manufacturers may develop expertise and invest in certain mass reduction strategies that may affect the approaches for mass reduction they consider and the associated costs. Manufacturers must also consider vehicle attributes like noise, vibration, and harshness (NVH), ride quality, handling, crash safety, repairability, and various acceleration metrics when considering how to implement any mass reduction strategy. These are aspects of performance, and any identified pathways to compliance are intended to maintain performance neutrality. Therefore, NHTSA does not consider mass reduction via elimination (*i.e.*, decontenting) of, for example, luxury items, such as climate control or interior vanity mirrors and leather padding, in the mass reduction pathways for this analysis.

The automotive industry uses different metrics to measure vehicle weight. Some commonly used measurements are vehicle curb weight,⁴³⁴ GVW,⁴³⁵ GVWR,⁴³⁶ gross combined vehicle weight (GCVW),⁴³⁷ and equivalent test weight,⁴³⁸ among others. The vehicle curb weight is the most 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.

NHTSA considered five levels of mass reduction technology (MR1 through MR5) that include increasing amounts of advanced materials and mass reduction techniques applied to the glider. NHTSA accounts for mass changes associated with powertrain changes separately because glider mass reduction can sometimes enable a smaller engine while maintaining performance neutrality. Smaller engines typically weigh less than bigger ones. NHTSA captures any changes in the resultant fuel savings associated with powertrain mass reduction and downsizing via the Autonomie simulation. Autonomie calculates a hypothetical vehicle's theoretical fuel mileage using a mass reduction for the vehicle curb weight equal to the sum of mass savings of the glider plus the mass savings associated with the downsized powertrain.

⁴³⁴ This is the weight of the vehicle with all fluids and components but without the drivers, passengers, and cargo.

⁴³⁵ This weight includes all cargo, extra added equipment, and passengers aboard.

⁴³⁶ This is the maximum total weight of the vehicle, passengers, and cargo to avoid damaging the vehicle or compromising safety.

⁴³⁷ This weight includes the vehicle and a trailer attached to the vehicle, if used.

⁴³⁸ 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."

Costs for the five levels of mass reduction are the same as those used in the 2022 final rule. The costs for the fifth level of mass reduction (MR5) technology are based on vehicle mass reduction design concept studies, teardown studies, and the NAS 2021 report.^{439,440} 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 mass reduction. These costs consider mass reduction of both primary and secondary structure, all of which are discussed in more detail below. NHTSA discusses the assumptions for the five mass reduction technology levels, the process used to assign initial analysis fleet mass reduction assignments, the effectiveness for applying mass reduction technology, and mass reduction costs below.

Note that in previous rules, there was a sixth level of mass reduction available as a pathway to compliance. For this analysis, this pathway was removed because it relied on extensive use of carbon fiber composite technology in primary structure to an extent that is only found in purpose-built racing cars and high-end sports cars costing at least hundreds of thousands of dollars. NHTSA determined that this technology is simply too expensive for use in vehicles purchased by typical consumers. Furthermore, there is significant competition from other industries (e.g., aerospace, wind, and sports) to obtain a scarce resource: dry carbon fibers. Given the relative scarcity of raw carbon fiber,⁴⁴¹ 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 mass reduction level would trigger rapid materials cost increases. However, as there are continuing efforts at the national laboratory, university, and industry levels to produce low cost, plentiful carbon fiber, NHTSA continues to monitor these efforts and would consider adding back the sixth level of mass reduction pathway in the future.

3.4.1. Mass Reduction in the CAFE Model

The amount of mass reduction technology existing in a given vehicle platform or applied to a given platform to meet compliance is expressed in terms of CAFE mass reduction levels, or mass reduction plus a number ranking. This is accomplished with five levels (MR0 – MR5). NHTSA considers mass reduction opportunities from the glider subsystems of a vehicle first, and then considers associated opportunities to downsize the powertrain, which NHTSA accounts for separately.⁴⁴² 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. NHTSA assumes 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

⁴³⁹ Singh, H. *et al.*, Mass Reduction of Light-Duty Vehicles for Model Years 2017-2025: Peer Review Comments Log, Report No. DOT HS 812 487, NHTSA: Washington, D.C. (2018), available at: https://www.nhtsa.gov/sites/nhtsa.gov/files/documents/13250f-peer_review_comment_resolution_document-final-112818-v3-tag.pdf (accessed: May 25, 2026) (hereinafter, “Singh *et al.* (2018)”).

⁴⁴⁰ Singh, H. *et al.*, Mass Reduction for Light-Duty Vehicles for Model Years 2017-2025, Report No. DOT HS 811 666, NHTSA: Washington, D.C., (2012), available at: https://static.nhtsa.gov/nhtsa/downloads/CAFE/2017-25_Final/811666.pdf (accessed: May 27, 2026) (hereinafter, “Singh *et al.* (2012)”).

⁴⁴¹ Sloan, J., 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: May 25, 2026).

⁴⁴² 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.

the powertrain depends on the powertrain size. Therefore, the weight of the glider impacts the weight of the powertrain.⁴⁴³

NHTSA uses glider weight to apply non-powertrain mass reduction technology in the CAFE Model and uses Autonomie simulations to determine the size of the powertrain and corresponding powertrain weight for the respective glider weight. The combination of glider weight (after mass reduction) and resized powertrain weight equal the vehicle curb weight. The cost and fuel-savings effectiveness calculation for curb weight mass reduction (described in a subsequent subchapter) occurs within Autonomie. The Autonomie simulation accounts for both the glider mass reduction and the powertrain mass reduction in its calculations of a vehicle’s fuel mileage.

3.4.1.1. Assumptions Behind the LD Mass Reduction Levels

The analysis considers five levels of mass reduction technologies that manufacturers could use to comply with CAFE standards. The magnitude of mass reduction in percent for each of these levels is shown in Table 3-70 as a percentage of vehicle glider weight (71 percent⁴⁴⁴ shown in the table) and curb weight for both passenger automobiles and non-passenger automobiles.

Table 3-70: Mass Reduction Technology Level and Associated Glider and Curb Mass Reduction

MR Level	Percent Glider Weight Reduction	Percent Vehicle Curb Weight (Passenger Cars) Reduction
MR0	0%	0.00%
MR1	5%	3.55%
MR2	7.5%	5.33%
MR3	10%	7.10%
MR4	15%	10.65%
MR5	20%	14.20%

Though there is a range of mass reduction technologies that manufacturers can apply to vehicles to achieve each of the five mass reduction levels, there are some general trends that are helpful to illustrate the more widely used approaches. Typically, MR0 reflects vehicles with widespread use of low carbon steel structures and body panels, and very moderate use of high-strength steel. MR0 reflects materials in use for average vehicles in the MY 2022 timeframe. MR1-MR3 can be achieved with a steel body structure. When going from MR1 to MR3, low carbon steel is expected to be replaced by high strength and then AHSS but using thinner gage panels. When going from MR3 to MR4, light metals like aluminum and magnesium may be required. This would start with using aluminum closure panels and, to get to MR4, the vehicle’s primary structure is likely mostly made from aluminum. In most cases, carbon fiber technology used in close-out panels like roofs and door skins is necessary to reach MR5, likely with a mix of either aluminum or magnesium, or both. Achieving several percentage points mass reduction past MR5 in 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

⁴⁴³ Because powertrains are sized based on the glider weight for the analysis, glider weight reduction beyond a threshold amount during a redesign will lead to resizing 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, electric motors, generator, high voltage wiring harness, high voltage connectors, inverter, battery management system(s), battery pack thermal system, and electric motor thermal system.

⁴⁴⁴ A 71-percent glider share is based on the average proportion of non-powertrain weight in an average passenger automobiles and average non-passenger automobile.

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 percent of the U.S. fleet. The only exception to this would have been the BMW i3, but production of the vehicle ceased in summer 2022.

As discussed further in Chapter 3.4.5, the cost studies that NHTSA uses 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. The mass reduction levels are loosely based on those studies' conclusions about what materials and components are required for each percent of mass reduction.

3.4.1.2. 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 mass reduction or secondary mass reduction. Primary mass reduction 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 mass reduction because each can be implemented independently. Other components and systems that may contribute to primary mass reduction include the vehicle body, chassis, and interior components.

When significant primary mass reduction occurs, other components designed based on the mass of primary components may be redesigned as well. An example of a subsystem where secondary mass reduction 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 mass reduction can be applied are wheels and tires.

The mass reduction levels assume primary and secondary mass reduction happen in a specific order.

Some mass reduction is more valuable to fuel savings than other mass reduction. All mass on a vehicle contributes to the translating mass of the vehicle (vehicle reference frames move relative to its surroundings). 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 contrasts with components like fuel tanks, windshields, and rear seats 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, the translational inertia of the vehicle as a whole and the rotational moment of inertia must be overcome. This requires more energy than if the components were just translating. Therefore, reducing the mass of these components provides an increased benefit.

As discussed further in Chapter 3.4.5, NHTSA develops the cost curves used in this analysis by sequencing the light-weighted components from the MY 2011 Honda Accord and MY 2014 Chevrolet Silverado studies^{445,446} based on cost effectiveness. The study assumes the vehicle body, chassis, interior, and other primary components are light-weighted first, followed then by light-weighting powertrain components and other secondary systems after there is sufficient primary mass reduction. Following the publication of these light-weighting studies, peer reviewers and manufacturers commented that many common components are shared across powertrains and vehicle models, such as drive axles, engine

⁴⁴⁵ Singh *et al.* (2012).

⁴⁴⁶ Singh *et al.* (2018).

cradles, and radiator engine support. These components are non-powertrain secondary mass reduction opportunities and 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 mass reduction, NHTSA agrees with peer reviewers and manufacturers that retaining a common design for all powertrain options avoids the proliferation of complexity to maintain economies of scale.

Based on the light-weighting studies, the cost curves apply secondary mass reduction to the brake system only after sufficient primary mass reduction. This allows the smaller brake system to provide safe braking performance and maintain mechanical functionality. This allows the agency to estimate the cost of mass reduction independently of the cost associated with downsized advanced engines and advanced transmissions. The cost of downsized advanced engines and transmissions are accounted for separately in the CAFE Model. Therefore, the five mass reduction levels included in this analysis appropriately reflect both primary and secondary mass reduction opportunities.

3.4.2. Mass Reduction Analysis for Light-Duty Fleet Assignment

To assign initial mass reduction levels (MR0 through MR5) for LDVs in the LD analysis fleet, NHTSA uses regression models previously developed during the 2015 rulemaking analysis, to estimate curb weight for each vehicle based on observable vehicle attributes. NHTSA uses MYs 2016-2017 analysis fleet data to update for some key models, like the aluminum-bodied Ford F-150.

To develop the curb weight regressions, NHTSA groups vehicles into three separate body design categories: 3-box, 2-box, and pickup as seen in Table 3-71. 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 3-71: Mass Reduction Body Style Sets

3-Box	2-Box	Pickup
Coupe Sedan Convertible	Hatchback Wagon Sport Utility Minivan Van	Pickup

NHTSA retains the MY 2015 regressions for 3-Box and 2-Box vehicles. Though 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 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 MY 2015 vehicle fleet analysis.

Starting with the 2022 final rule, NHTSA upgraded the pickup category regression in response to comments on the 2016 Draft TAR. NHTSA estimated a new regression with EPA MY 2014 CAFE compliance data and added pickup bed length as an independent variable. This upgrade also included the addition of the largely aluminum F-150. Looking back at the MY 2014 data for the pickup truck

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 MY 2015 pickup truck 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.

NHTSA leverages many documented variables in the LD analysis fleet as independent variables in the regressions. Continuous independent variables are used for the LD regression model and include footprint (wheelbase x track width) and powertrain peak power. Binary independent variables include strong HEV (yes or no), PHEV (yes or no), AWD (yes or no), RWD (yes or no), pickup bed length (for the pickup truck regression only) and convertible (yes or no). For PHEV 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.⁴⁴⁷

The regression results for 3-Box, 2-Box, and Pickup trucks are shown in Table 3-72, Table 3-73, Table 3-74.

Table 3-72: 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
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 3-73: Regression Statistics for Curb Weight (lbs.) for Pickup Vehicles

Observations	312
Adjusted R Square	0.84

⁴⁴⁷ The Hyundai Santa Cruz and Ford Maverick are two such FWD pickup trucks but share platforms with the Hyundai Tucson and Ford Bronco Sport, respectively. Because mass reduction is applied at the platform level, they can be counted as AWD without affecting the mass reduction regression modelling.

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)	-	-	-	-	-	-
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 3-74: 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
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)	-	-	-	-	-	-

Each of the three regressions produce outputs effective for identifying vehicles with a significant amount of mass reduction 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.

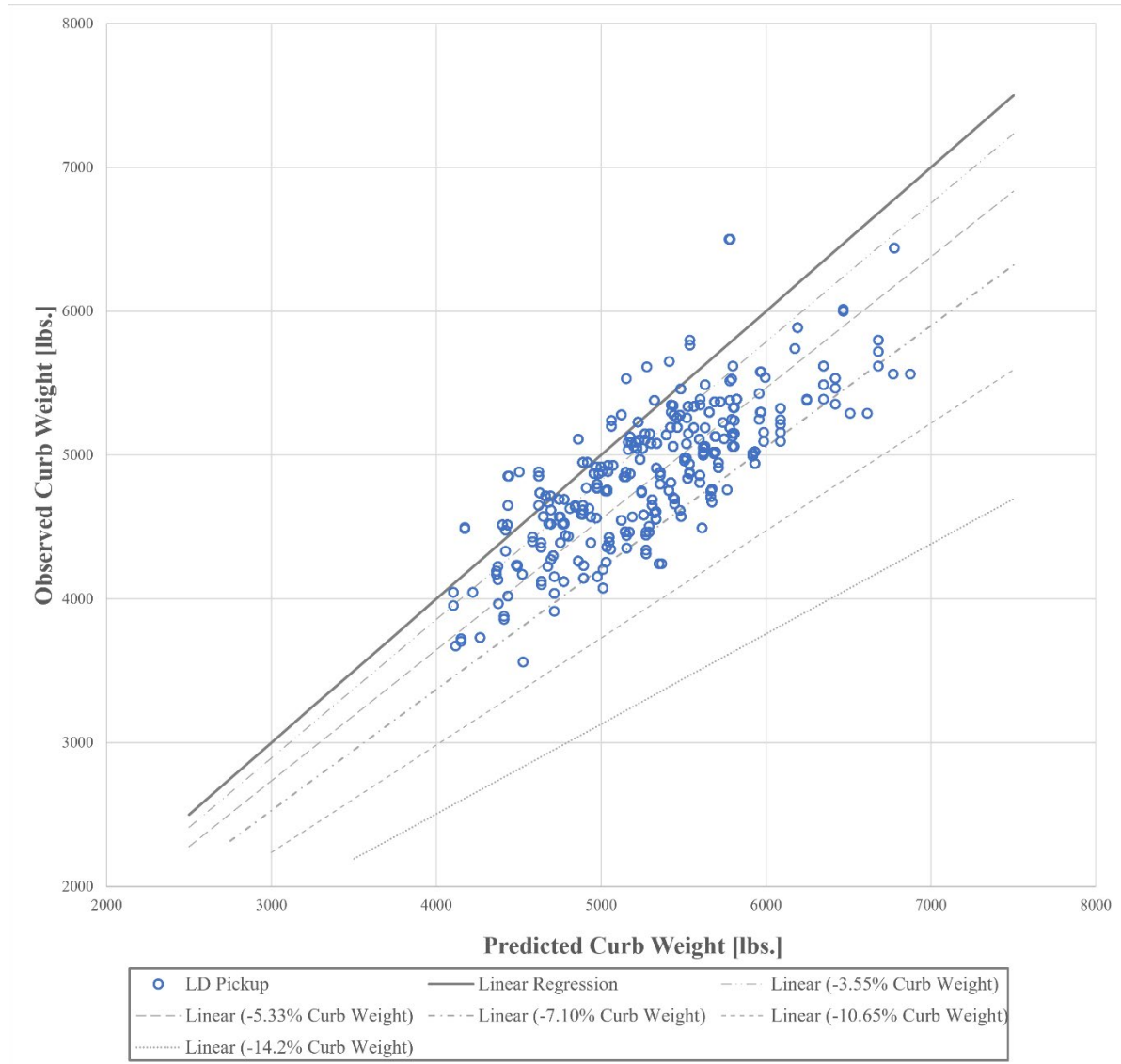
NHTSA does not conduct a tear down study and detailed cost assessment for every vehicle in every model year. After reviewing many vehicles in the 2024 MY Fleet and noting their construction methods, we observe that some vehicles contain advanced light-weight technology yet only achieve MR0 or MR1 (*i.e.* small residuals).

Industry engineers 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.⁴⁴⁸ 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. NHTSA continues to look for practical ways to improve the assessment of mass reduction content and the forecast of incremental mass reduction costs for each vehicle for future analyses.

Figure 3-17 shows results from the LD pickup truck regression on predicted curb weight versus actual curb weight. Points above the solid regression line represent vehicles heavier than predicted (with lower mass reduction technology levels); points below the solid regression line represent vehicles lighter than predicted (with higher mass reduction technology levels). The dashed lines in Figure 3-17 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.

⁴⁴⁸ Stoy, A., Carbon Core: 2016 BMW 7-Series Gets Carbon-Fiber Implants, last revised: Apr. 21, 2015, available at: <https://www.autoweek.com/news/a1868071/carbon-core-2016-bmw-7-series-gets-carbon-fiber-implants/> (accessed: May 25, 2026).

Figure 3-17: Observed Curb Weight vs. Predicted Curb Weight for the MY 2022 Analysis Fleet for 71 Percent Glider Share for Pickup Truck



For points where actual curb weight is below the predicted curb weight, NHTSA uses the residual as a percentage of predicted weight to get a sense for the level of current mass reduction 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 MY 2022 fleet.^{449,450}

Generally, residuals of regressions as a percentage of predicted weight stratify vehicles by mass reduction level appropriately. 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 mass reduction. Most vehicles with the largest negative residuals adopt advanced weight savings technologies at the most expensive end of the cost curve. There are, however, vehicles that achieve high mass reduction levels

⁴⁴⁹ 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.

⁴⁵⁰ NHTSA, 2022 fleet Market Data Input File is available at https://static.nhtsa.gov/nhtsa/downloads/CAFE/2024-FRM-LD-2b3-2027-2035/Central-Analysis/Central_Analysis_Inputs.zip (accessed: May 14, 2026)

without the use of advanced light-weighting technologies. For instance, some cargo vans achieve high mass reduction levels because heavy luxury items such as sound deadening, power adjustable seats, sunroofs, *etc.* have been left out during their design. This results in low weight relative to other vehicles with high luxury item content and similar footprints.

To validate the residuals, NHTSA reviews the results for all vehicle platforms in the fleet. NHTSA then compares the assigned mass reduction values to information about the vehicles collected from websites and digital brochures to determine if the assigned mass reduction values are reasonable. From these information sources, NHTSA collects vehicle dimensional information as well as the construction materials and techniques used to make the vehicles to determine whether the assigned mass reduction values are reasonable. NHTSA compares that information with the designs and materials used in the mass reduction feasibility and cost studies summarized in Chapter 3.4.5. This comparison shows consistent agreement with the technology levels derived from the regression analysis. NHTSA believes the regression methodology is a technically sound approach for estimating mass reduction levels in the analysis fleet.

Manufacturers generally apply mass reduction 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; therefore, conducting the regression analysis at the platform level leads to more accurate estimates for the real-world vehicle platform mass reduction levels. The platform approach 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. This minimizes the impact of any outlier vehicle configurations.

Table 3-75 shows the regression results to select vehicles in the LD passenger car fleet.

Table 3-75: 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
Lamborghini	Urus	-21.8	MR5
Bugatti	Chiron	-21.2	MR5
Hyundai	Elantra	-14.2	MR4
Lamborghini	Aventador	-13.8	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
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

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. Though some technologies (*e.g.*, low rolling resistance tires) are nearly “bolt-on” technologies, others involve substantial changes to the structure and design of the vehicle and often affect all vehicle models that share that platform. In most cases, mass reduction technologies are applied to platform level components, and 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. Like 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 mass reduction present in the analysis fleet. If there is a tie, the CAFE Model begins mass reduction technology on the vehicle with the highest sales in MY 2042. If there remains a tie, the Model begins by choosing the vehicle with the highest MSRP in MY 2024. As the Model applies technologies, it effectively levels up all variants on a platform to the highest level of mass reduction technology on the platform. Therefore, if the platform leader is already at MR3 in MY 2024, and a “follower” starts at MR0 in MY 2024, the follower receives MR3 at its next redesign (unless the leader is redesigned again before that time and further increases the mass reduction level associated with that platform, then the follower would receive the new mass reduction level).

Understanding NHTSA’s handling of vehicles that traditionally operated on the same platform but had a mix of old and new platforms in production at the time NHTSA created the analysis fleet is important for understanding the analysis fleet mass reduction assignments, and for understanding adoption features as well. For example, the Honda Civic and Honda CR-V are LDVs that traditionally share the same platform. In MY 2016, Honda redesigned the Civic and updated the platform to include many mass reduction technologies. Also in MY 2016, Honda continued to build the CR-V on the previous generation platform that did not include many of the mass reduction technologies on the MY 2016 Civic. In MY 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 mass reduction 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 mass reduction technology on the new shared platform at the first available redesign year.

An LD auto manufacturer’s strategy to achieve mass reduction consistent with MR5 requires extensive use of carbon fiber technologies in the vehicles’ “hang-on” components, such as fenders, decklids, and

hoods. Moreover, MR5 requires the 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 are likely higher for carbon fiber production than current automotive steel production, due to fiber handling complexities. In addition, R&D overhead increases 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 enable direct accounting for the stranded capital associated with a transition away from stamped sheet metal construction to molded composite materials construction. For decades, 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. Though this is possible, 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 passenger cars is also the availability of dry carbon fibers. Dry carbon fibers are produced by exposing acrylic fibers to heat that burns off unneeded organic molecules attached to their carbon backbones and by stretching the fibers to straighten out the carbon bonds. This process, known as “pyrolysis” is slow and energy intensive. The world’s highest producing pyrolysis lines are in Japan, China, the United States, and, to a lesser extent, Europe. Altogether, about 161,200 metric tons are produced annually.⁴⁵¹ The supply is predicted to increase at a compound annual growth rate (CAGR) of roughly 6 percent.⁴⁵²

Demand for this limited amount of material from the aerospace, wind and defense industries is extreme. Only around 17.8 percent⁴⁵³ of this annual production is currently available to the entire international auto industry. If the entire U.S. fleet is about 21 percent of the world fleet, it is reasonable to assume that a little over 6000 metric tons of dry carbon fiber is available to auto manufacturers for the U.S. fleet.

Assuming that vehicles achieving MR5 use carbon fiber composite technology to lighten closure and hang-on panels (door outers, deck lids, fenders, hoods, and roof panels), it means that on average there would be roughly 22.2 kg of carbon fiber per-vehicle.⁴⁵⁴ Taking all these calculations and assumptions into account, it follows that at the time of writing there is only enough carbon fiber for the U.S. fleet to support building roughly 271,441 cars per year to reside at or be elevated to the MR5 level. NHTSA anticipates the number of vehicles to reside at the MR5 level to increase over time, commensurate with the grow rate of the global supply of dry carbon fibers. This number assumes the composite materials from which the vehicles are made contain 72-percent dry carbon fiber by mass and 28-percent polymer matrix materials.

⁴⁵¹ Sloan, J., Plant Tour: Hexcel, Salt Lake City, Utah, U.S., last revised: May 22, 2020, available at: <https://www.compositesworld.com/articles/plant-tour-hexcel-salt-lake-city-utah-us> (accessed: May 25, 2026).

⁴⁵² GlobeNewswire, Global Carbon Fiber Market to Hit Market Size of USD 52.16 Billion by 2050: Astute Analytica, last revised: Apr. 3, 2024, available at: <https://www.globenewswire.com/news-release/2024/04/03/2857049/0/en/Global-Carbon-Fiber-Market-to-Hit-Market-Size-of-USD-52-16-Billion-By-2050-Astute-Analytica.html> (accessed: May 25, 2026).

⁴⁵³ BMW i3 Cost Analysis, Zone 1: Body Structure, Munro & Associates Inc. 2016.

⁴⁵⁴ See Calculation CF for Cars and Trucks ii.xlsx available in the rulemaking docket by filtering for Supporting & Related Material.

As a result of the limited availability of carbon fiber, its high cost and non-conventional methods of manufacturing components made from carbon fiber components, high-volume platforms may adopt its use decades from now. Consequently, NHTSA applies platform size caps to the application of MR5. Because mass reduction 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 the selected volume cap number of vehicles or fewer are eligible to apply MR5 toward CAFE compliance in the CAFE Model.⁴⁵⁵ Platforms representing high-volume sales, like a Chevrolet Traverse, for example, where hundreds of thousands are sold per year, are therefore blocked from having MR5 technology applied to in the CAFE Model.

To date, the BMW i3, which was produced between 2013 and 2021, is the highest volume platform to incorporate the use of carbon fiber composites in its primary structure fully. At that point in time, the average yearly production volume was roughly 27,777 vehicles per year.⁴⁵⁶ This then serves as an appropriate lower bound for the platform cap.

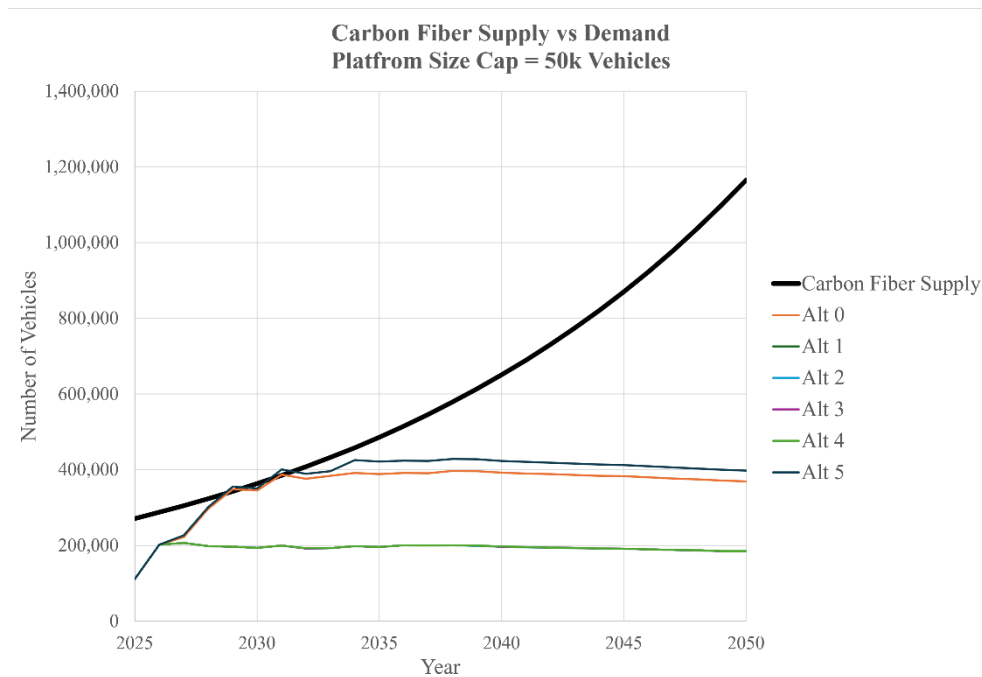
For the standard-setting years, the platform size cap is determined as follows. The compounding growth rate of carbon fiber production is plotted on a graph in Figure 3-18 showing the number of vehicles (equivalent to mass of carbon fiber) versus year. Simultaneously plotted on this graph is the number of vehicles eligible (*i.e.*, the aggregate platform size cap) for MR5 technology versus year for a wide range of alternative sweeps. Such plots were created for platform size caps from 5,000 vehicles to 50,000 vehicles by increments of 2,500 vehicles. Initially at a cap of 5,000 vehicles, the line representing the number of vehicles eligible for MR5 was hundreds of thousands of vehicles below the carbon fiber supply line (as expressed in number of vehicles). However, at a platform size cap of around 45,000, the eligible vehicles line crosses over and above the carbon fiber supply line for the two most stringent alternatives during the standard-setting years. That is, supply outstrips demand just above a platform size cap of 45,000 vehicles for the two most stringent alternatives. Therefore, for this analysis NHTSA set the MR5 platform size cap at 50,000 vehicles.

Note there are no phase-in caps or materials availability limits for LD mass reduction levels MR1, MR2, MR3, or MR4.

⁴⁵⁵ 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.

⁴⁵⁶ Boudway, I., BMW's i3 Is Already a Cult Classic, last revised: Dec. 12, 2022, available at: <https://www.bloomberg.com/news/features/2022-12-12/bmw-s-discontinued-i3-is-already-an-ev-cult-classic> (accessed: May 25, 2026).

Figure 3-18: Graph of the Supply and Demand of Dry Carbon Fiber of the U.S. Auto Industry



Another way NHTSA updated MR5 limitations was to use skip logic to block vehicles classified as non-passenger automobiles (based on the new non-passenger automobile criteria that goes into effect in MY 2030) from using MR5 as a pathway to compliance. The vehicles that remain non-passenger automobiles following reclassification in MY 2030 have physical requirements for their frame, axles, suspensions, and drivetrains to perform the non-passenger utility required to meet the updated classification criteria. Further discussion of these design considerations can be found in Final TSD Chapter 2.7. The number of pounds that must be removed from a vehicle to reduce its mass by one percent linearly increases as the weight of the vehicles increases, and vehicles possessing significant non-passenger capability to utilize a greater portion of their total weight to drivetrain, axle, suspension, and frame components that are not suitable for MR5 content. This means that significantly more carbon fiber is required in the other areas of the vehicle to achieve a percent reduction in total vehicle weight. Therefore, the estimated 22.2 kg average dry carbon fiber content per vehicle mentioned above likely underestimates the actual amount of dry carbon fiber needed to achieve MR5 on larger, heavier automobiles that have a focus on higher utility and durability, like those in the reclassified non-passenger automobile fleet. Due to the limited supply of carbon fiber and the additional carbon fiber that would be required to achieve MR5 for heavier vehicles, NHTSA blocks vehicles in the non-passenger automobile fleet, which are generally heavier than passenger automobiles, from using MR5 in the compliance simulation.

3.4.4. Mass Reduction Effectiveness

Argonne 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.⁴⁵⁷ An accurate list of initial component weights that make up each vehicle subsystem is important for precisely estimating the effectiveness of different levels of mass reduction. Autonomie considers potential mass reduction opportunities based on this list.

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.⁴⁵⁸ 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 plumbing, heat exchanger, or pop-off valve) has 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. The powertrain mass accounting is separate from the application and accounting for mass reduction technology levels (MR0-MR5), which are applied to the glider in the simulations. Similarly, Autonomie accounts for battery and motor mass used in HEVs and EVs separately. This secondary mass reduction is discussed further below.

3.4.4.1. Glider Mass and Mass Reduction

In the Autonomie simulations, mass reduction 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 3-76 shows the average mass for each subsystem and the glider share for each of the vehicle classes for all powertrain combinations.

Table 3-76: 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%
Mid-size Non-Performance	650.00	200.00	175.00	60.13	25.00	30.26	54.00	1194.40	1611.24	74.13%
Mid-size Performance	650.00	200.00	200.00	65.12	28.00	40.25	57.00	1240.37	1734.89	71.50%
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%

⁴⁵⁷ CAFE Analysis Autonomie Documentation Chapter titled “Autonomie Simulation Process.”

⁴⁵⁸ Depending on the powertrain combination, the total curb weight of the vehicle includes glider, engine, transmission or battery pack and motor(s).

Mid-size SUV Non-Performance	650.00	200.00	200.00	70.13	30.00	30.26	66.00	1246.40	1754.57	71.04%
Mid-size 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%
Heavy-Duty Pickup	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, NHTSA consults with Argonne to examine glider weight data available in the A2Mac1 database.⁴⁵⁹ 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.⁴⁶⁰ 147 vehicles between MYs 2014-2016 are analyzed, covering 35 vehicle brands with different powertrain options representing a wide array of vehicle classes, to determine the percentage of the vehicle comprising the glider.⁴⁶¹

The agency's passenger car and light truck light-weighting studies examine mass reduction in the body, chassis, interior, brakes, steering, electrical accessory, and wheels subsystems and have developed costs for light-weighted components in those subsystems. NHTSA believes it is appropriate to include all subsystems as available for mass reduction of the glider. Therefore, all systems are included for the analysis of glider weight using the A2Mac1 database.

3.4.4.2. Powertrain Mass Reduction

NHTSA accounts for all mass reduction due to powertrain improvements separately from glider mass reduction. Autonomie considers several components for powertrain mass reduction, including engine downsizing, fuel tank, exhaust systems, and cooling system light-weighting.⁴⁶²

Regarding the LDV 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 mass reduction would provide an additional 3-percent increase in fuel economy.⁴⁶³ 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 mass reduction of 10 percent or greater is applied to the glider mass, or when one powertrain architecture replaces another architecture.

⁴⁵⁹ A2Mac1: Automotive Benchmarking (proprietary data), last revised: <https://portal.a2mac1.com/> (accessed: May 25, 2026).

⁴⁶⁰ Bill of material (BOM) is a list of the raw materials, sub-assemblies, parts, and quantities needed to manufacture an end-product.

⁴⁶¹ See The Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule for Model Years 2021-2026 Passenger Cars and Light Trucks, Docket No. NHTSA-2018-0067-1490.

⁴⁶² Though NHTSA does not account for mass reduction in transmissions, NHTSA does reflect design improvements as part of mass reduction when going from, for example, an older AT6 to a newer AT8 that has similar if not lower mass.

⁴⁶³ NRC (2015).

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,⁴⁶⁴ to account for the difference in weight for different engine types for LDVs. 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, NHTSA uses this relationship to estimate mass for all engine types regardless of technology type (*e.g.*, VVL and direct injection). NHTSA applies 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 2 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 methodology helps account for the cost of the glider and cost of the engine and transmission in the CAFE Model.

Similarly, engine downsizing and powertrain secondary mass reduction is possible after a certain level of mass reduction is incorporated in the glider. The Autonomie simulations account for the aggregate of both primary and secondary glider mass reduction, and separately for powertrain mass.

Note that secondary mass reduction is integrated into the mass reduction cost curves. The NHTSA studies 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 secondary mass reduction for the brake system is only applied after there has been sufficient primary mass reduction.

NHTSA enhances the accuracy of estimated engine weights by creating multiple curves to represent naturally aspirated engine designs and turbocharged engine designs for gasoline fuels and diesel fuels separately.⁴⁶⁵ 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 have lower weight due to having fewer engine cylinders. A naturally 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.

NHTSA believes it is reasonable to allow engine resizing for LDVs upon adoption of 7.1-, 10.7-, and 14.2- (see Table 3-70) percent curb weight reduction, but not at 3.6 and 5.3 percent.⁴⁶⁶ 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 mass reduction, or complete powertrain changes, appropriately match the typical engine displacement increments that are available in a manufacturer's engine portfolio.

⁴⁶⁴ CAFE Analysis Autonomie Documentation Chapter titled "Engine Weight Determination."

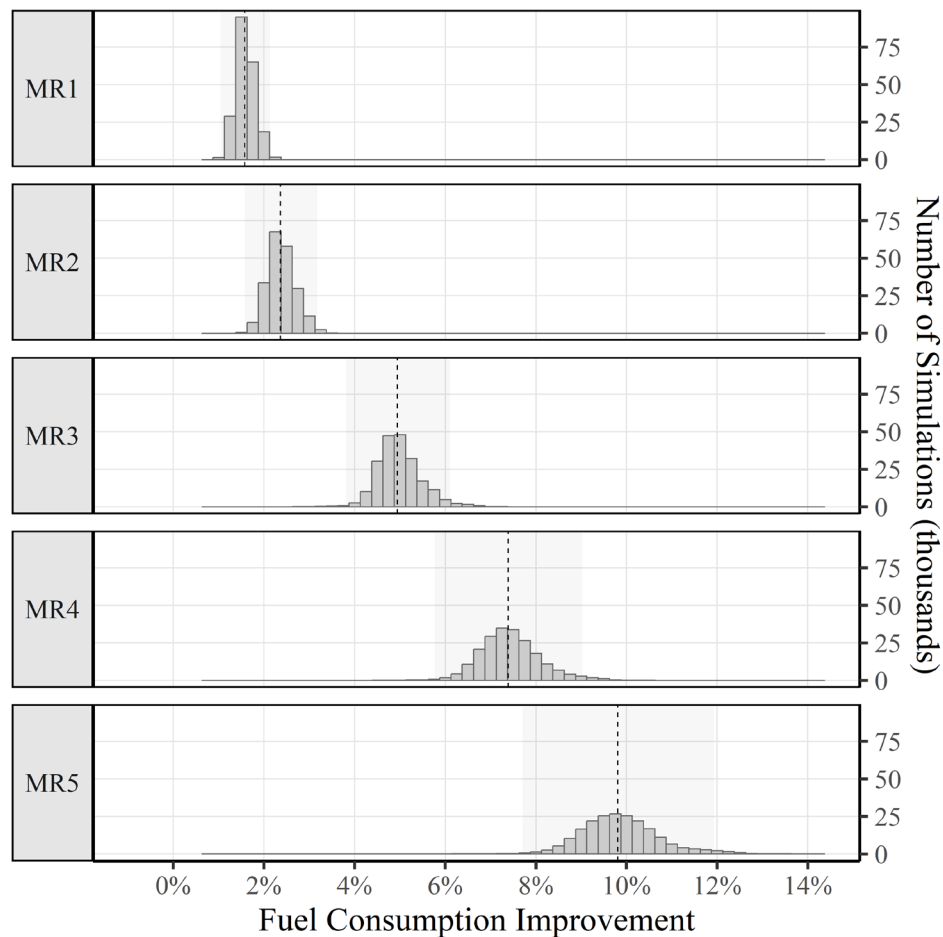
⁴⁶⁵ Chapter "Vehicle Component Weight Selection" of the CAFE Analysis Autonomie Documentation.

⁴⁶⁶ These curb weight reductions equate to the following levels of mass reduction as defined in the analysis: MR3, MR4, and MR5, but not MR1 and MR2; additional discussion of engine resizing for mass reduction can be found in Chapter 2.3.

3.4.4.3. The Summary of Mass Reduction Technology Effectiveness

The range of effectiveness values for the mass reduction technologies for the ten LDV technology classes are shown in Figure 3-19 for the standard-settings scenarios. Autonomie simulates all possible combinations of technologies for fuel consumption improvements. For a few technology combinations, mass reduction 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 3-19 shows the range of improvements based on the full range of other technology combinations for the LD fleet.

Figure 3-19: Mass Reduction Technology Effectiveness Values for All Vehicle 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.⁴⁶⁷ 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

⁴⁶⁷ 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.

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.

NHTSA uses a revised costing method for mass reduction in this analysis. NHTSA improves the Model to include a bracketed costing approach. During the period of public comment for the 2024 final rule, multiple commenters pointed out that not all the mass removed in engineering a vehicle to achieve the maximum weight savings level, MR5, would cost the rates associated with MR5. In contrast, in previous analyses, all mass reductions required to reach a given mass reduction level would be costed at a rate for the maximum level achieved. For example, if 100 lbs. were saved to reach MR1, and MR1 was costed at a rate of X_1 dollars per pound saved, then the cost to achieve MR1 was $100 * X_1$. Likewise, if 200 lbs. were saved to go from MR0 to MR2 and the costs associated with MR2 was X_2 dollars per pound saved, then the cost to go from MR0 to MR2 would be $200 * X_2$. That is, mass reduction costing was modeled to pay MR2 rates for all 200 lbs. savings required to achieve MR2, rather than a combination of MR1 and MR2 costing rates.

A more realistic method for costing mass reduction levels, and the one NHTSA uses in this analysis, is using a bracket approach. Using brackets is a progressive system in which the level of costing rate progressively increases as higher levels of mass reduction are achieved for a given OEM's vehicle platform. Low level mass reduction falls into a costing bracket with a relatively low costing rate, while higher levels of mass reduction fall into brackets with higher costing rates. The higher costing rates are only charged for the incremental mass reduction required in going from one mass reduction level to the next one higher. For example, when going from MR0 to MR2 the cost is tallied at one rate for the first 5-percent mass savings (MR0 to MR1) and then at another higher rate for the next 2.5-percent mass savings (MR1 to MR2). The sum of these two is the price tag to go from MR0 to MR2. In the previous example, this means that the cost to go from MR0 to MR2 would be $100 * X_1 + 100 * X_2$, where $X_1 < X_2$. NHTSA uses a similar costing approach in going from MR0 to MR3, from MR0 to MR4, and so on.

The price tag to go from MR0 to MR5 that NHTSA uses is:

$$\sum_{i=1}^5 M_i X_i$$

where:

$$X_1 < X_2 < X_3 < X_4 \ll X_5$$

and where M_i is the mass savings to get from the $i-1$ mass reduction level to the i th mass reduction level.

3.4.5.1. Updates to MR5 Costs Based on Carbon Fiber Studies

For this analysis, NHTSA relies on the cost estimates for carbon fiber construction that the National Academies detailed in the 2021 Assessment of Technologies for Improving Fuel Economy of LDVs – Phase 3.⁴⁶⁸ 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. To use this cost in the CAFE Model it is put in terms of dollars per pound saved. Using an average vehicle curb weight of 4000 lbs., a 71-percent 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. The NAS study claims that the carbon fiber substitution for steel in an automotive component produces a 50-percent mass reduction.

⁴⁶⁸ 2021 NAS report, at p. 7–242–3.

Combining all this together, carbon fiber technology offers weight savings at \$24.60 per pound saved. This dollar per pound savings figure is 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.⁴⁶⁹ The analysis uses this cost for achieving MR5. Just to reiterate, this cost rate is only used for incremental mass reduction going from MR4 to MR5.

Table 3-77 shows the cost values used in the CAFE Model for the LD fleet with MR1-4 costs based on the cost curves developed from the MY 2011 Honda Accord and MY 2014 Chevrolet Silverado studies, and the updated MR5 values that account for the updated carbon fiber costs from the 2021 NAS report. All tables assume a 71-percent glider share.

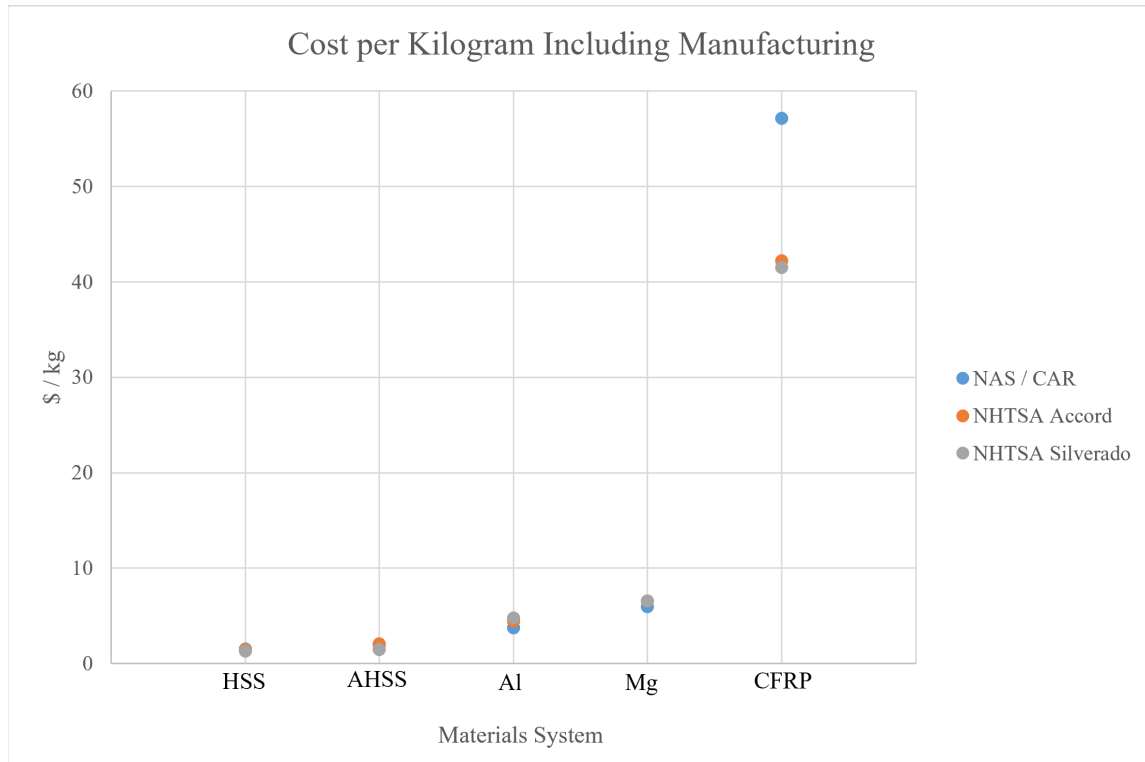
Table 3-77: Mass Reduction DMCs (2024\$) in CAFE Model for Small Car, Small Car Performance, Medium Car, Medium Car Performance, Small SUV, Small SUV Performance, Medium SUV, Medium SUV Performance, Pickup, Pickup High Towing (HT)

	Percentage Reduction in Glider Weight	Percentage Reduction in Curb Weight	Cost of Mass Reduction (2024\$/lbs.)
MR0	0.00%	0.00%	\$0.00
MR1	5.00%	3.55%	\$0.51
MR2	7.50%	5.33%	\$0.97
MR3	10.00%	7.10%	\$1.38
MR4	15.00%	10.65%	\$1.68
MR5	20.00%	14.20%	\$40

There is a dramatic increase in cost going from MR4 to MR5 for all classes of vehicles. However, though the increase in cost going from MR4 to MR5 is dramatic, the MY 2011 Honda Accord study, the MY 2014 Chevrolet Silverado study, and the 2021 NAS report all include a steep increase to achieve the highest levels of mass reduction technology, as seen in Table 3-77. Figure 3-20 shows the cost per kilogram for various materials used for mass reduction 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 mass reduction to reach MR5 requires a majority of secondary structure and possibly 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 aluminum, magnesium, or steel as shown in Figure 3-20.

⁴⁶⁹ See MR5 CFRP Cost Increase Calculator.xlsx available in the rulemaking docket by filtering for Supporting & Related Material.

Figure 3-20: 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 NASEM,⁴⁷⁰ the NHTSA Accord Study,⁴⁷¹ and the NHTSA Silverado⁴⁷²



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.⁴⁷³ 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. The aerodynamic drag of a vehicle is often expressed as the product of the two values, $C_d A$, which is also known as the drag

⁴⁷⁰ 2021 NAS report, at p. 7–242–3.

⁴⁷¹ Singh *et al.* (2012), at p. 145, Figure 138.

⁴⁷² Singh *et al.* (2018), at p. 102, Figure 113.

⁴⁷³ Butcher *et al.*, Optimizing the University of Wisconsin's Parallel Hybrid-Electric Aluminum Intensive Vehicle, SAE 2000-01-0593, Warrendale, PA: SAE International, (2000), available at: <https://doi.org/10.4271/2000-01-0593> (accessed: May 25, 2026).

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.⁴⁷⁴

Manufacturers reduce aerodynamic drag by either 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. Examples 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 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. Though 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 NHTSA assigns 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

NHTSA uses four levels of aerodynamic improvements in the CAFE Model. The levels are associated 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). Technology pathway logic for levels of aerodynamic improvement, which are shown in Figure 3-21, consists of a linear progression, with each level superseding all previous levels.⁴⁷⁵

Though the four levels of aerodynamic improvements are technology-agnostic, NHTSA provides 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 includes an extensive review of production vehicles utilizing these technologies, and industry comments.^{476,477} This is intended to show

⁴⁷⁴ Pannone, G., Technical Analysis of Vehicle Load Reduction Potential for Advanced Clean Cars, Final Report, California Air Resources Board and The California Environmental Protection Agency: Sacramento, CA, (2015), available at: https://ww2.arb.ca.gov/sites/default/files/2020-04/13_313_ac.pdf (accessed: May 25, 2026) (hereinafter, “Pannone (2015)”). The graph on page 20 shows how at higher speeds the aerodynamic force becomes the dominant load force.

⁴⁷⁵ CAFE Model Documentation Technology Constraints (Supersession and Mutual Exclusivity) Section.

⁴⁷⁶ Larose, G. *et al.*, 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): pp. 772 – 84 (2016), available at: <https://doi.org/10.4271/2016-01-1613> (accessed: Apr. 30, 2026).

⁴⁷⁷ *Ibid.*

potential ways that manufacturers can achieve each aerodynamic improvement level; however, manufacturers may implement different combinations of aerodynamic technologies to achieve improvement over their baseline vehicles. Table 3-78 shows the aerodynamic technologies that a manufacturer can use to achieve 5-, 10-, 15-, and 20-percent improvements in passenger cars and SUVs. Table 3-78 shows the aerodynamic technologies that a manufacturer can use to achieve 5-, 10-, and 15-percent improvements in pickup trucks.

As discussed further in Chapter 3.5.4, NHTSA restricts the Model from applying AERO20 to pickup trucks, which is why there is no pathway to AERO20 shown in Table 3-79. Though a manufacturer could apply some aerodynamic improvement technologies across vehicle classes, like active grille shutters (used in the 2015 Chevrolet Colorado),⁴⁷⁸ NHTSA believes 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 can reach each AERO level but would not necessarily be required to use the technologies.

Table 3-78: 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%

Table 3-79: 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%

⁴⁷⁸ Chevrolet, Chevrolet Product Information: 2015 Chevrolet Colorado (2015).

	Underbody Cover (Incl. Rear axle cladding)	3.0%
AERO15	Active Grill Shutters	3.0%
	Extend Air dam	2.0%

3.5.2. Aerodynamic Technologies in the Baseline Fleet

NHTSA uses 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 2024 LD fleet, are provided in Table 3-80. 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.

Table 3-80: Penetration Rates of Aerodynamic Drag Reduction Levels in the 2024 LD Fleet

Aero Technology	Technology Description	Standard-Setting Analysis	
		Sales Volume	Penetration Rate
AERO0	Baseline aero	3,355,312	24.5%
AERO5	Aero level 1 (5% drag reduction)	4,479,851	32.7%
AERO10	Aero level 2 (10% drag reduction)	5,153,969	37.6%
AERO15	Aero level 3 (15% drag reduction)	325,906	2.4%
AERO20	Aero level 4 (20% drag reduction)	391,182	2.8%

NHTSA assigns a body style to every vehicle in the LD fleet. Available body styles include convertible, coupe, sedan, hatchback, wagon, SUV, pickup, minivan, and van.⁴⁷⁹ These assignments do not necessarily match the body styles that manufacturers use for marketing purposes. Instead, NHTSA makes these assignments based on engineering judgement and the categories used in the modeling. In addition, NHTSA considers how a body style 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. NHTSA harmonizes the assignment of body types with the Autonomie simulation vehicle technology classes to the fullest extent possible.⁴⁸⁰

For this analysis, NHTSA classifies the level of aerodynamic technology application based on the vehicle’s coefficient of drag. A baseline coefficient of drag is determined and represents the minimum

⁴⁷⁹ See Market Data Input File.

⁴⁸⁰ See Table 2-4 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.

AERO0 coefficient value. This means if the vehicle has a coefficient of drag greater than the established baseline value, it is classified as AERO0 tech level. For the LD analysis fleet, NHTSA also determines an average baseline drag coefficient for each body style using manufacturers published MY 2015 drag coefficients data, these values are shown in Table 3-81.

For each of the AERO technology levels, a maximum and minimum coefficient of drag value is determined, such that if the vehicle's coefficient level was less than the maximum value but greater than the minimum value, it is 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 reaches 0.317 or less 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, NHTSA uses 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. NHTSA uses engineering judgment to assign an AERO level where NHTSA does not find a publicly available drag coefficient. If NHTSA is unable to manually determine an AERO level, NHTSA uses values received from manufacturers along with previous rulemaking analyses, such as data from the MY 2016 or MY 2020 fleet baseline fleet.^{481,482} The MY 2016 or MY 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 3-81 for LDVs. 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 LD baseline fleet.

Baseline drag coefficients are utilized in the 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 3-81: Aerodynamic Application by Manufacturer as a Percent of MY 2024 LD Sales Used in this Analysis

Manufacturer	AERO0	AERO5	AERO10	AERO15	AERO20
BMW	32.6%	14.9%	31.7%	9.0%	11.8%
Mercedes-Benz	23.3%	0.9%	21.9%	1.9%	52.0%
Stellantis	72.1%	12.7%	4.6%	10.6%	0.0%
Ford	4.8%	0.0%	90.7%	4.5%	0.0%
GM	3.8%	25.3%	70.9%	0.0%	0.0%
Honda	3.3%	35.8%	58.3%	2.7%	0.0%
Hyundai	1.1%	65.6%	12.9%	0.0%	20.4%
Kia	27.3%	56.4%	13.5%	0.0%	2.8%
JLR	33.0%	20.7%	7.9%	17.8%	20.6%
Mazda	1.9%	72.9%	21.6%	0.0%	3.6%

⁴⁸¹ See 83 FR 42986 (Aug. 24, 2018). The MY 2016 fleet was built to support the 2018 NPRM.

⁴⁸² See 87 FR 25710 (May 2, 2022). The MY 2020 fleet was built to support the 2022 final rule.

Mitsubishi	13.2%	55.6%	31.1%	0.0%	0.0%
Nissan	28.2%	46.8%	24.9%	0.1%	0.0%
Subaru	29.0%	44.0%	27.0%	0.0%	0.0%
Toyota	55.2%	31.3%	11.0%	2.5%	0.0%
Volvo	4.9%	61.9%	32.5%	0.8%	0.0%
VWA	23.7%	52.1%	24.1%	0.1%	0.0%
INEOS	100.0%	0.0%	0.0%	0.0%	0.0%
Ferrari	0.0%	0.0%	100.0%	0.0%	0.0%

3.5.3. Aerodynamic Technology Adoption Features

NHTSA uses a relative performance approach to assign a 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, NHTSA assumes all technologies that improve aerodynamic drag forces do so by reducing C_d while maintaining frontal area.

For this LD analysis, the following adoption features apply: the highest levels of AERO are not considered for certain body styles. In these cases, this means that NHTSA does 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. NHTSA also deems 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 3-78, 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, and wagons and does not consider AERO15 and AERO20 for minivans as a potential pathway to compliance in response to regulatory alternatives.

NHTSA does not allow application of AERO15 and AERO20 technology to vehicles with more than 780 HP. Performance ICE vehicles are the vehicles that inform this threshold. The agency recognizes 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 ICE vehicles without reducing HP. Only 2,518 units of sales volume in the baseline fleet include limited application of aerodynamic technologies due to ICE vehicle performance.⁴⁸³

Note that while many aerodynamic features that contribute to drag reduction (*e.g.*, active grill shutters) are considered off-cycle technologies, AERO levels and the off-cycle program are modeled separately for the analysis. For further discussion of off-cycle technologies, see Chapter 3.7.

3.5.4. Aerodynamic Technology Effectiveness

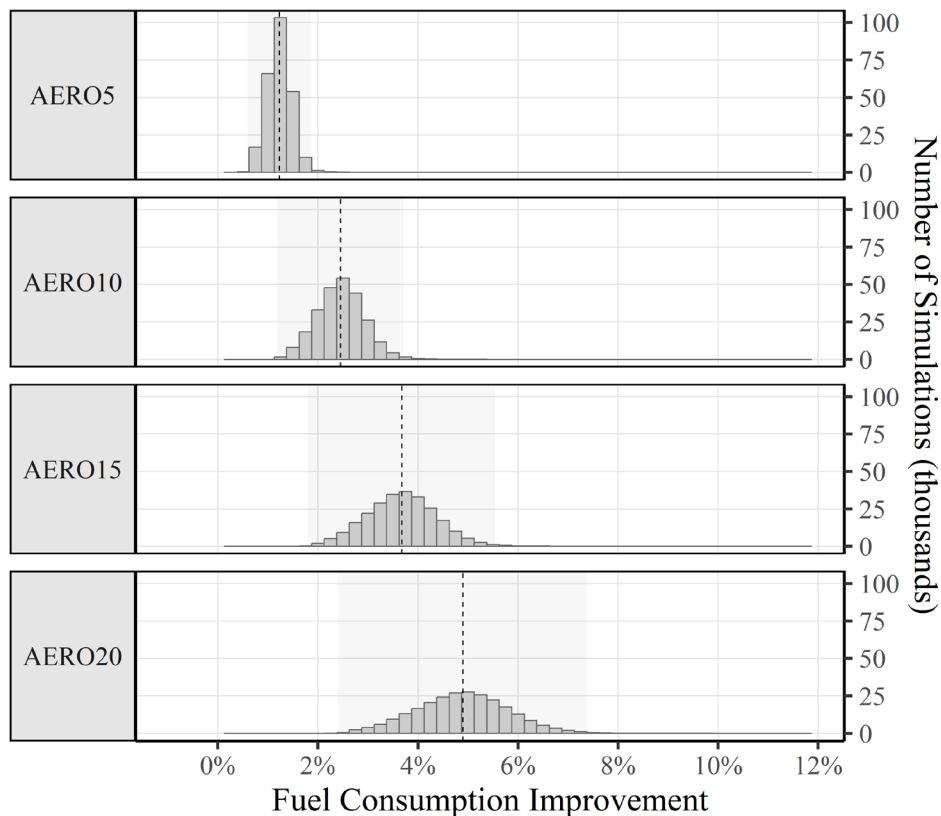
Effectiveness values for aerodynamic technologies are shown in Figure 3-21 for LDVs. See Chapter 3.5.1 for a discussion about what each aerodynamic technology represents and how it is considered. The

⁴⁸³ See the Market Data Input File.

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 (e.g., passenger space, ingress/egress ergonomics, and cargo space).

The effectiveness values shown in Figure 3-21 are 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, NHTSA uses the change in fuel consumption values between entire technology keys,⁴⁸⁴ and not the individual technology effectiveness values. Using the change between whole technology keys captures the complementary or non-complementary interactions among technologies.

Figure 3-21: LD 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 rule⁴⁸⁵ and again in the 2022 final rule⁴⁸⁶ and 2024 final rule.⁴⁸⁷ The cost estimates are based on CBI submitted by the automotive industry in advance of the 2018 CAFE NPRM, and on the agency's

⁴⁸⁴ Technology key is the unique collection of technologies that constitutes a specific vehicle see Chapter 3.

⁴⁸⁵ See the Regulatory Impact Analysis (RIA) accompanying the 2020 final rule, Chapter VI.C.5.e.

⁴⁸⁶ [2022 final rule link]

⁴⁸⁷ [2024 final rule link]

assessment of manufacturing costs for specific aerodynamic technologies. The 2018 preliminary regulatory impact analysis (PRIA) contains discussion of the cost estimates.⁴⁸⁸ NHTSA did not receive comments from stakeholders regarding the costs established in the 2018 PRIA during the MYs 2024-2026 standards analysis. NHTSA continues to use the established costs in this analysis. These costs have been adjusted to reflect the 2024-dollar values, as shown in Table 3-82.

For LD 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 3-82.

Table 3-82 shows the initial DMC values for aerodynamic improvement technologies in MY 2024 reported in 2024\$. The table also shows the total costs for the technologies across multiple model years, also in 2024 dollars. 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 that are assumed to have been available longer. See the Technologies Input File for all costs across all model years.

Table 3-82: DMC and Total Costs of Aerodynamic Improvement Technology for LDVs (in 2024\$) - Includes RPE and Learning Effects

Aero Improvements for Passenger Cars and SUV	DMC (2024\$)	Total Cost: Including RPE and Learning Factors (2024\$)	
		MY 2022	MY 2030
0%	\$0	\$0	\$0
5%	\$55	\$63	\$56
10%	\$113	\$129	\$114
15%	\$283	\$182	\$162
20%	\$738	\$321	\$286

3.6. Tire Rolling Resistance

ROLL 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 and thus have less traction. Wet roads can rapidly lower tire temperature and, therefore, such road conditions can also affect deformation and recovery time.

⁴⁸⁸ See the PRIA accompanying the 2018 NPRM, Chapter 6.3.10.1.2.1.2 for a discussion of these cost estimates.

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 the 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, belts and elastomer portions 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. That is, less deformation means less energy lost and less rolling resistance.⁴⁸⁹ 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 on past CAFE rules stating that improving tire rolling resistance would be detrimental to grip. In recent years it has become possible to engineer rolling resistance and grip separately, and to mitigate issues related to stopping distance without raising rolling resistance.⁴⁹⁰ Tire manufacturers have done this by selecting different materials (*e.g.*, various types of either silica or Silanes as reinforcing fillers, 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. Though 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 either vehicle suspension tuning or suspension design, or both, to mitigate any potential impact on those attributes. Separately, low rolling resistance tires are also increasingly available from aftermarket tire vendors.

NHTSA continues to assess the potential impact of tire rolling resistance changes on vehicle safety. NHTSA is following rolling resistance technology trends and industry developments applicable to LDVs. In the NAS special report on Tires and Passenger Vehicle Fuel Economy,⁴⁹¹ it was noted that national crash data do not provide data about tire structural failures specifically related to tire rolling resistance and NHTSA is unaware of any other data connecting low rolling resistance tires to increased accident or fatality rates.

Brake performance compliance test data are helpful to show trends. Stopping distance has not changed in the last ten years,⁴⁹² during which time many manufacturers have installed low rolling resistance tires in their fleet. Brake performance compliance test data are helpful to show these trends. Manufacturers are successful in improving rolling resistance while maintaining stopping distances through tire design, tire

⁴⁸⁹ Akutagawa, K., Technology for Reducing Tire Rolling Resistance, *Japanese Society of Tribologists*, Vol. 12(3): pp. 99 – 102 (2017), available at: https://www.jstage.jst.go.jp/article/trol/12/3/12_99/_pdf (accessed: May 25, 2026).

⁴⁹⁰ Snyder, J., A Big Fuel Saver: Easy-Rolling Tires (But Watch Braking), 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: May 25, 2026).

⁴⁹¹ Transportation Research Board, Tires and Passenger Vehicle Fuel Economy: Informing Consumers, Improving Performance, Special Report 286, The National Academies Press: Washington, D.C., (2006), available at: <https://nap.nationalacademies.org/catalog/11620/tires-and-passenger-vehicle-fuel-economy-informing-consumers-improving-performance> (accessed: May 25, 2026).

⁴⁹² NHTSA Office of Vehicle Safety Compliance, Compliance Test Report Database, last revised: 2025, available at: <https://www.nhtsa.gov/compliance/> (accessed: May 25, 2026).

materials, or braking system improvements like those discussed above. 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.⁴⁹³

The following subchapters discuss levels of ROLL technology that NHTSA applies in the CAFE Model, how the technology is assigned in the analysis fleet, including adoption features specified to maintain performance, effectiveness, and cost.

3.6.1. Tire Rolling Resistance Reduction Technologies

NHTSA considers three levels of low rolling resistance tire technology for LDVs in this analysis. 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 3-83 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 3-83: 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

NHTSA uses an industry-average RRC reference value of 0.009 based on a CONTROLTEC study prepared for the CARB,⁴⁹⁴ 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 0.009.⁴⁹⁵ The CONTROLTEC study compares 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 0.0092,⁴⁹⁶ compared to the average of 0.009 from CONTROLTEC.

The Joint TSD for 2012 final rule and the TSD for the 2020 final rule state that tire technologies that enable rolling resistance improvements of 10 and 20 percent have been in existence for many years.⁴⁹⁷ Achieving improvements of up to 20 percent involves optimizing and integrating multiple technologies, with a primary contributor being the adoption of silica tread technology. Tire suppliers indicate that

⁴⁹³ The results of these tests are presented in Docket No. NHTSA-2021-0053-0010, Memo to Docket - Rolling Resistance Phase One and Two.

⁴⁹⁴ Pannone (2015).

⁴⁹⁵ 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.

⁴⁹⁶ Pannone (2015).

⁴⁹⁷ EPA, Joint Technical Support Document: Final Rulemaking for 2017-2025 Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards, EPA-420-R-12-901, p. 3 – 210 (2012), available at: <https://nepis.epa.gov/Exe/ZyPDF.cgi/P100F1E5.PDF?Dockey=P100F1E5.pdf> (accessed: May 25, 2026) (hereinafter, “EPA 2012”).

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).^{498,499} At the cutting edge, scientists use computer simulations and advanced molecular imaging techniques to understand better 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 allow 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.^{500,501,502}

NHTSA included ROLL30 in the analysis for the first time for the 2024 final rule based on the increasing application of the technology by OEMs. NHTSA received comments on both the 2020 final rule and 2022 final rule indicating that ROLL30 should be included based on the availability of the technology and the possibility that there would be additional improvement but did not include it in the analyses for those rulemakings due to lack of widespread commercial adoption. Comments NHTSA received during the comment period for the 2022 final rule also reflected the application of ROLL30 by OEMs, though they discouraged considering the technology due to high cost and possible wet traction reduction. The increasing use of ROLL30 application by OEMs,^{503,504,505} and material selection make it possible to design low rolling resistance independent of tire wet grip (discussed above). NHTSA considers ROLL30 as a viable future technology during the rulemaking period.

NHTSA believes that the tire industry is in the process of moving automotive manufacturers towards higher levels of rolling resistance technology in the vehicle fleet. NHTSA believes that at this time, the emerging tire technologies that would achieve 30-percent improvement in rolling resistance, like

⁴⁹⁸ Terrill E. R. *et al.* Dynamic Mechanical Properties of Passenger and Light Truck Tire Treads, DOT HS 811 270, Washington, D.C.: NHTSA (2010), available at: https://downloads.regulations.gov/NHTSA-2008-0121-0055/attachment_1.pdf (accessed: May 25, 2026) (hereinafter, “Terrill *et al.* (2010)”).

⁴⁹⁹ Van Hoek, J. W. *et al.*, Implications of the Use of Silica as Active Filler in Passenger Car Tire Compounds of Their Recycling Options, *Materials*, Vol. 12(5): p. 725 (2019), available at: <https://doi.org/10.3390/ma12050725> (accessed: May 25, 2026).

⁵⁰⁰ Akutagawa K., Technology for Reducing Tire Rolling Resistance, *Japanese Society of Tribologists*, Vol. 12(3): pp. 99 – 102 (2017), available at: https://www.jstage.jst.go.jp/article/trol/12/3/12_99/pdf (accessed: May 25, 2026).

⁵⁰¹ Terrill *et al.* (2010).

⁵⁰² Amino, N., Friction & Rolling Resistance of Tyres, *Nippon Gomu Kyokaishi*, Vol. 88(2): pp. 37 – 42 (2015), available at: <https://doi.org/10.1177/0307174X1504200910> (accessed: May 25, 2026).

⁵⁰³ See Evaluation of Rolling Resistance and Wet Grip Performance of OEM Stock Tires Obtained From New Car Assessment Program (NCAP) Crash Tested Vehicles Phase One and Two, Memo to Docket - Rolling Resistance Phase One and Two, Docket No. NHTSA-2021-0053-0010.

⁵⁰⁴ Pannone (2015).

⁵⁰⁵ Evans L. R. *et al.*, NHTSA Tire Fuel Efficiency Consumer Information Program Development: Phase 2 – Effects of Tire Rolling Resistance Levels on Traction, Treadwear, and Vehicle Fuel Economy, DOT HS 811 154, NHTSA: Washington, D.C. (2009), available at: https://downloads.regulations.gov/NHTSA-2008-0121-0035/attachment_1.pdf (accessed: May 25, 2026).

changing tire profile, stiffening tire walls, or adopting improved tires along with active chassis control,⁵⁰⁶ among other technologies, will be available for commercial adoption in the fleet during this rulemaking timeframe. As a result, NHTSA considers a 30-percent reduction in rolling resistance technology for the LD analysis.

3.6.2. Tire Rolling Resistance Analysis Fleet Assignments

Tire rolling resistance is not a part of tire manufacturers' publicly released specifications making it difficult to assign this technology to the analysis fleet. Manufacturers offer multiple wheel and tire packages for the same nameplates, further increasing the complexity of this assignment. NHTSA employs 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), NHTSA received RRC values from vehicle manufacturers. NHTSA carries over rolling resistance assignments for nameplates where manufacturers have submitted data on the vehicles' rolling resistance values, even if the vehicle is redesigned.
- NHTSA sponsors a tire rolling resistance study and uses those values in place of any older or missing values.⁵⁰⁷
- NHTSA assigns ROLL0 to vehicles for which no information is available from either previous manufacturer submissions or the NHTSA study data.
- All vehicles under the same nameplate are assigned the same rolling resistance technology level even if manufacturers outfit different trim levels with different wheels and tires. NHTSA uses the same tires for the same vehicle under the same nameplate based on NHTSA's experience and information provided by manufacturers.

Table 3-84 shows the distribution of ROLL technology for the LD fleets. This table shows the LD fleet now adopts some form of rolling resistance technology. NHTSA needs further information from manufacturers or other sources to account for any additional ROLL technology in the fleet.

Table 3-84: Distribution of Tire Rolling Resistance Technology in the MY 2024 Analysis Fleet

Technology	Standard-Setting Analysis
ROLL0	54.9%
ROLL10	13.0%
ROLL20	28.4%
ROLL30	3.7%

3.6.3. Tire Rolling Resistance Adoption Features

The Model applies rolling resistance technology with either a vehicle refresh or redesign. NHTSA recognizes that some manufacturers prefer to maintain specific tires with a higher RRC for some

⁵⁰⁶ Davari, M., Rolling Resistance and Energy Loss in Tyres, Svea Seminar, (2015), available at: <https://docslib.org/doc/4775729/rolling-resistance-and-energy-loss-in-tyres-mohammad-mehdi-davari-mmmdavari-kth-se-kth-vehicle-dynamics-department-of-aeronautical-and-vehicle-engineering> (accessed: May 25, 2026).

⁵⁰⁷ See 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, Docket No. NHTSA-2021-0053-0010.

performance cars and SUVs. Performance cars and SUVs have higher torque, which causes tire slip. These performance vehicles prefer higher rolling resistance tires to avoid tire slip. NHTSA applies adoption features based on three different levels of HP limitations: 350HP, 405HP, and 500HP, based on the vehicle's body style (*e.g.*, pickup truck, SUV, or wagon). NHTSA applies 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 3-85 When Can ROLL Technology Be Applied, Based on Vehicle Body Style and Engine Horsepower

Technology	LD		
	≥350	≥405	≥500
Engine HP	≥350	≥405	≥500
ROLL0	All body styles	All body styles	All body styles
ROLL10	All body styles	All body styles	-Pickup truck
ROLL20	All body styles	-Pickup truck -SUV -Van -Minivan	No body styles
ROLL30	-Pickup truck -Sport Utility -Van -Minivan	No body styles	No body styles

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 automobile or non-passenger automobile). For example, as shown in the table, ROLL20 can be applied to all LD pickup trucks and vans that have an engine HP lower than 500HP.

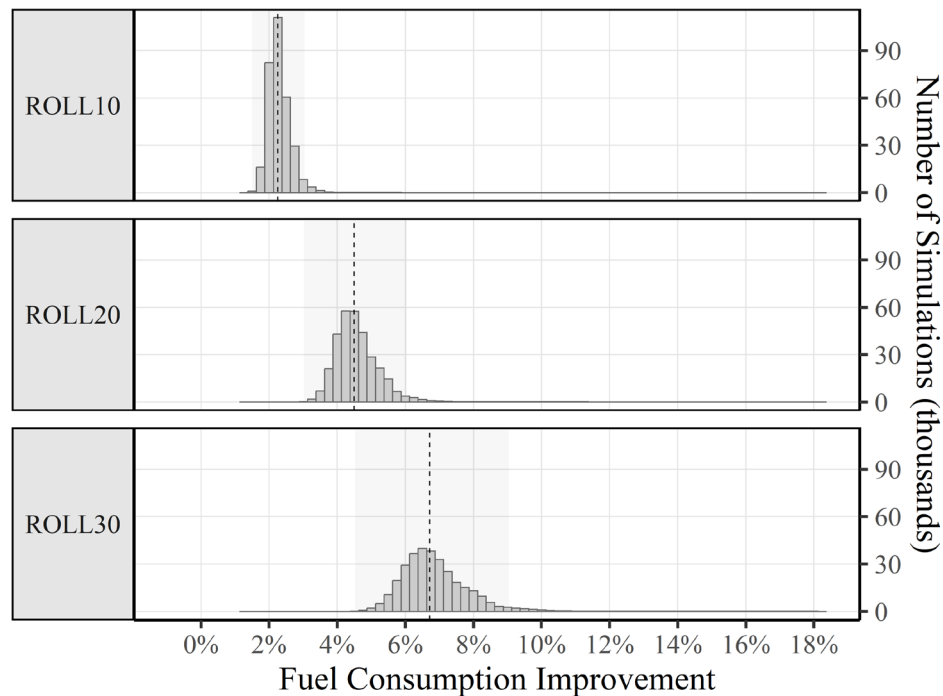
3.6.4. Tire Rolling Resistance Effectiveness

As discussed above, based on the CONTROLTEC study, a thorough review of CBI submitted by industry, and a review of other literature, NHTSA uses a reference rolling resistance value of 0.009. To achieve ROLL10, the tire rolling resistance must be at least 10 percent better than 0.009 (.0081 or better). To achieve ROLL20, the tire rolling resistance must be at least 20 percent better than 0.009 (.0072 or better). To achieve ROLL30, the tire rolling resistance must be at least 30 percent better than 0.009 (.0063 or better).

NHTSA determines effectiveness values for rolling resistance technology adoption using Autonomie modeling. Figure 3-22 below shows 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,⁵⁰⁸ and not the individual technology effectiveness values. Using the change between whole technology keys captures the complementary or non-complementary interactions among technologies.

⁵⁰⁸ A technology key is the unique collection of technologies that constitutes a specific vehicle see Chapter 2.3.6.

Figure 3-22: LD Roll Technology Effectiveness Values for All Vehicle Technology Classes



3.6.5. Tire Rolling Resistance Costs

The DMC and learning rates used for ROLL10 and ROLL20 technology are the same as those used for prior analyses,⁵⁰⁹ and the DMC is updated to 2024 dollars. In the absence of ROLL30 DMCs from tire manufacturers, vehicle manufacturers, or studies, to develop the DMC for ROLL30 NHTSA extrapolates the DMCs for ROLL10 and ROLL20 and then updates them to reflect 2024 dollars. If NHTSA receives updated information from tire or vehicle manufacturers on this value, NHTSA will update it for future analyses.

Table 3-86 shows the different levels of ROLL technology cost.

Table 3-86: Cost for Tire Rolling Resistance Technologies Relative to ROLL0

Technology	Tire Rolling Resistance Technology Costs (2024\$)
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⁵⁰⁹ See NRC/NAS Special Report 286, Tires and Passenger Vehicle Fuel Economy: Informing Consumers, Improving Performance (2006), available at: <https://onlinepubs.trb.org/Onlinepubs/sr/sr286.pdf> (accessed: May 25, 2026); NHTSA, Corporate Average Fuel Economy for MY 2011 Passenger Cars and Light Trucks, Final Regulatory Impact Analysis (2009), at V-137, available at: https://www.nhtsa.gov/sites/nhtsa.gov/files/cafe_final_rule_my2011_fria.pdf (accessed: May 25, 2026); EPA, Joint Technical Support Document: Rulemaking to Establish Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards, EPA-420-R-10-901, p. 3-77 (2010), available at: https://www.nhtsa.gov/sites/nhtsa.gov/files/final_joint_tsd.pdf (accessed: May 25, 2026); NHTSA, 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, EPA-420-D-16-900, EPA: Washington, D.C., pp. 5-153, 154 and 5-419 (2016), available at: <https://www.nhtsa.gov/sites/nhtsa.gov/files/draft-tar-final.pdf> (accessed: May 25, 2026). 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.

	Direct Manufacturing Cost	Total Cost for MY 2024 (includes RPE and Learning)
ROLL0	\$0.00	\$0.00
ROLL10	\$6.34	\$7.12
ROLL20	\$49.57	\$46.79
ROLL30 ⁵¹⁰	\$98.65	\$95.47

3.7. Simulating AC Efficiency and Off-Cycle Technologies

3.7.1. AC Efficiency and Off-Cycle Technologies in the CAFE Program

In the last several rulemaking analyses, the CAFE Model has evaluated the benefits of AC efficiency and OC technologies. These technologies provide fuel economy benefits in real-world vehicle operation that are not fully captured using the required 2-cycle (*i.e.*, FTP and HWFET) test procedures used to measure fuel economy.⁵¹¹ 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 lower the load the compressor places on the engine or battery storage system, resulting in better fuel efficiency. AC efficiency technologies include, but are not limited to, blower motor controls, internal heat exchangers, and improved condensers/evaporators. Off-cycle technologies include, but are not limited to, thermal control technologies, high-efficiency alternators, and high-efficiency exterior lighting.⁵¹²

As a means of encouraging the use of these technologies, EPA provides vehicle manufacturers with the option to generate fuel consumption improvement values (FCIVs) for OC technologies and improved AC efficiency systems in its CAFE test procedure regulations.⁵¹³ These provisions were based on and referenced EPA’s provisions for generating credits (in grams of CO₂ per mil) for OC technologies and improved AC efficiency systems in its CO₂ program. Though EPA rescinded its CO₂ program regulations and the provisions allowing manufacturers to generate AC efficiency and OC credits in that program, EPA did not remove the provisions allowing manufacturers to generate FCIVs for the CAFE program in light of this active rulemaking.⁵¹⁴

FCIVs are not “credits,” but instead increase a manufacturer’s 2-cycle fuel economy performance values, which are used to demonstrate compliance with NHTSA’s fuel economy standards.⁵¹⁵ EPA applies FCIVs when it calculates a fleet’s final average fuel economy performance prior to reporting it to NHTSA. EPA only calculates and applies FCIVs at a manufacturer’s fleet level, and the improvement is based on the

⁵¹⁰ Roll30 technology is only applied to light-duty vehicles.

⁵¹¹ 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. . . . [T]he 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.”).

⁵¹² 40 CFR 510-12(c)(3)

⁵¹³ 40 CFR 600.510-12(c).

⁵¹⁴ 91 FR 7686, Feb. 18, 2026.

⁵¹⁵ 49 U.S.C. 32904(c), (d), and (e). EPCA granted EPA authority to establish fuel economy testing and calculation procedures. See preamble Section VI for more information.

volume of the manufacturer’s fleet that contains qualifying technologies.⁵¹⁶ Per its regulation, to calculate the FCIV value EPA converts the CO₂ reduction for the technologies in grams per mile into an equivalent gallon-per-mile improvement.

There is one pathway that manufacturers can use to generate FCIVs for the application of AC efficiency technologies.⁵¹⁷ EPA’s regulations provide a technology menu that specifies improvement values for the addition of specific technologies and specifies testing requirements to confirm that the technologies provide emissions reductions when installed as a system on vehicles.⁵¹⁸ A vehicle’s total AC efficiency FCIV is calculated by summing the individual values for each efficiency-improving technology used on the vehicle, as specified in the AC menu or by the test result.⁵¹⁹ The total AC efficiency FCIV sum for each vehicle is capped at 5.0 grams/mile for passenger automobiles and 7.2 grams/mile for non-passenger automobiles.⁵²⁰ EPA’s regulations do not currently phase out or eliminate FCIVs for AC efficiency technologies. However, starting in MY 2027, manufacturers may generate FCIVs only for vehicles propelled by internal combustion engines.

Currently, there are three pathways that manufacturers can use to claim benefits associated with off-cycle technologies per EPA’s regulations for calculating fuel economy for the CAFE program. First, manufacturers can use a predetermined list or “menu” of credit values (in g CO₂/mi) that EPA has approved for specific off-cycle technologies, which is set to phase out between MYs 2031-2033.⁵²¹ EPA finalized provisions to retain the current 10 g/mile menu cap through MY 2030, with a phase-out of 8/6/0 g/mile in MYs 2031-2033.⁵²² Second, manufacturers can use 5-cycle testing to demonstrate a credit value that accurately represents the benefits of the technology; the three additional test cycles (beyond the standard two test cycles) allow manufacturers to demonstrate emissions benefits over some elements of real-world driving that are not captured by the 2-cycle compliance tests (*e.g.*, high speeds, rapid accelerations, or hot and cold temperatures), which is set to end in MY 2027. Lastly, manufacturers can use a notice-and-comment process to seek EPA approval to use an alternative methodology, separate from the “menu” and 5-cycle methodology, to demonstrate a representative credit value, which is set to end starting in MY 2027.⁵²³

For the standard-setting analysis, NHTSA is removing AC efficiency and OC technologies from consideration starting in MY 2028, which is the first year in which a removal of FCIVs could go into effect.⁵²⁴ NHTSA accomplishes this in the CAFE Model by setting the maximum allowable FCIV to 0 g CO₂/mi in the Scenarios Input File. See Section VI of the preamble for a more detailed discussion of how AC efficiency and OC FCIVs affect compliance with NHTSA’s fuel economy standards.

⁵¹⁶ 40 CFR 600.510-12(c).

⁵¹⁷ 40 CFR 86.1868-12, as referenced by 40 CFR 600.510-12.

⁵¹⁸ See 40 CFR 86.1868-12(e) through (g).

⁵¹⁹ See 40 CFR 86.1868-12(g)(2)(iii).

⁵²⁰ See 40 CFR 86.1868-12(b)(2).

⁵²¹ See 40 CFR 86.1869-12(b). The TSD for the 2012 final rule for MY 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 off-cycle technologies that meet or exceed those expectations in order to achieve the real-world benefits of off-cycle technologies from the menu.

⁵²² 89 FR 27842.

⁵²³ See 40 CFR 86.1869-12(d).

⁵²⁴ 49 U.S.C. 32904(d).

The next subchapters discuss how the CAFE Model applies costs and simulates the effectiveness of AC efficiency and OC technology adjustments.

3.7.2. AC Efficiency and Off-Cycle Effectiveness Modeling in the CAFE Model

3.7.2.1. Collecting and Maintaining AC Efficiency and Off-Cycle Technology Data

For model years through MY 2027, the CAFE Model uses the AC efficiency and OC FCIVs to develop a final CAFE performance value that has been adjusted to account for the improvements associated with those technologies. In the analysis, the CAFE Model runs the compliance simulation for MY 2027 and applies conventional technologies to simulate compliance with the applicable fuel economy standard first and then applies AC efficiency and OC FCIVs. That is, conventional technologies are applied to each manufacturer's vehicles 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 the adoption of conventional technology and the AC efficiency and OC technology is limited to MY 2027 and earlier in the CAFE Model. The CAFE Model applies technologies and flexibilities in a way that both minimizes cost and allows the manufacturer to meet their standards without over or under-complying.⁵²⁵ For model years through MY 2027, NHTSA applies FCIVs in the CAFE Model in this way because the AC and OC technologies are generally more cost effective to achieve compliance than other technologies. For the compliance simulation for MY 2027, NHTSA allows 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. The details of this assessment (and the calculation) are further discussed in the CAFE Model Documentation.⁵²⁶

To determine how manufacturers might adopt AC efficiency and OC technologies for model years through MY 2027, NHTSA uses data from manufacturers' MY 2024 mid-model year CBI compliance reports.⁵²⁷ NHTSA used manufacturers' MY 2024 AC efficiency and OC FCIVs they achieved via the "menu" as a starting point for each regulatory class, and then held those values constant from MYs 2024-2031 for the No-Action Alternative and through MY 2027 for action alternatives. Unlike previous versions of this analysis, NHTSA did not extrapolate the MY 2024 values to future model years. Instead, the Model assumes that FCIVs for MY 2027 will be the same as they were for MY 2024. Manufacturers have been able to settle in on a level of AC efficiency and OC technologies that maximize their return on investment (ROI); therefore, NHTSA does not anticipate a significant increase in manufacturers' AC efficiency and OC FCIVs between MYs 2024-2027, for any regulatory category.

As mentioned in Chapter 2.1.5, the Scenarios Input File contains AC efficiency and OC adjustment caps (in g CO₂/mi), which the CAFE Model uses to limit the level of adjustments the Model can apply for a given model year. As discussed in more detail in preamble Section II, to assess the effect of removing AC efficiency and OC FCIVs in the regulatory alternatives, NHTSA zeroes out values in the Scenarios Input File. See the Market Data Input File for the AC efficiency and OC credit FCIVs (in g CO₂/mi) that apply to compliance simulations for model years in which FCIVs may be generated. See Chapter 2 S5.4 of the CAFE Model Documentation for more discussion on how the CAFE Model incorporates AC efficiency, and OC technology achievable values and credit caps into its compliance modeling.

⁵²⁵ See CAFE Model Documentation.

⁵²⁶ CAFE Model Documentation, Chapter 2 S5.

⁵²⁷ 49 U.S.C. 32907.

3.7.3. AC Efficiency and Off-Cycle Costs

The CAFE Model applies AC efficiency and OC technologies independent of the technology pathways detailed in Chapter 3.1 through Chapter 3.6. Instead, the Model applies those technologies based on the adjustment values shown in the “Credits and Adjustments” worksheet of the Market Data Input File and limited by the associated credit caps in the Scenarios Input File. Similarly, the CAFE Model accounts for the AC efficiency and OC costs independent of the technologies applied via the technology pathways. For that reason, NHTSA places AC efficiency and OC technology total costs in the Scenarios Input File rather than the Technologies Input File. Below, NHTSA describes how NHTSA develops the AC efficiency and OC technology total costs that support the analysis.

In its 2010 FRIA,⁵²⁸ EPA estimated that AC efficiency technologies would have a DMC of \$51.00 per vehicle (in 2005\$) in MY 2012. In their 2010 Final TSD, EPA and NHTSA described AC efficiency technologies as having time-based learning that reduces costs by 3 percent per year.⁵²⁹ In their 2012 Final TSD,⁵³⁰ 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 MY 2017.

To facilitate adding the new DMC for AC efficiency technologies to the initial estimate, NHTSA uses GDP Price Deflators to convert the initial DMC from 2005\$ to 2021\$ and the new DMC from 2010\$ to 2021\$. NHTSA then applies a learning factor of 0.85⁵³¹ to translate the effective date of the initial DMC from MY 2012 to MY 2017. Next, NHTSA adds 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 MY 2017. NHTSA then uses GDP Price Deflators to convert the total DMC to \$87.87 per vehicle (in 2024\$) in MY 2017. Table 3-87 contains a summary of the AC efficiency technology DMCs.

Table 3-87: AC Efficiency Technology DMCs for PCs and LTs

	Initial	Initial	New	Initial	New	Total	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	DMC [2024\$ / veh] in MY 2017
AC Efficiency	N/A	\$51.00	\$15.00	\$58.79	\$18.51	\$77.30	\$87.87

As previously mentioned, the DMCs for AC efficiency technologies are in dollars per vehicle; however, the CAFE Model requires a unit DMC (in dollars per grams of CO₂/mile) as an input. To convert the DMCs (in dollars per vehicle) for AC efficiency technologies to a unit DMC (in dollars per grams of CO₂/mile), NHTSA divides them by an appropriate credit value (in grams of CO₂/mile). In their 2012 Final TSD, EPA and NHTSA estimate an average AC efficiency credit value of 5.0 grams of CO₂/mile for passenger cars and light trucks in MY 2017. Using this credit value, NHTSA calculates the unit DMC

⁵²⁸ EPA, Final Rulemaking to Establish Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards Regulatory Impact Analysis for MYs 2012-2016, last revised: 2010, available at: <https://nepis.epa.gov/Exe/ZyPDF.cgi/P1006W9S.PDF?Dockey=P1006W9S.pdf> (accessed: May 25, 2026) (hereinafter, “EPA (2010)”).

⁵²⁹ EPA (2010).

⁵³⁰ EPA (2012).

⁵³¹ Using the learning curve from the 2010 Final TSD, NHTSA started with a learning factor of 1.00 in MY 2012 and reduced it 3 percent per year to MY 2010, which yielded a learning factor of 0.85 in MY 2017.

for AC efficiency technologies to be \$15.46 per gram of CO₂/mile for passenger cars and light trucks, in 2021\$ in MY 2017.

Next, NHTSA applies a learning factor of 0.94⁵³² to the AC efficiency unit DMC to translate it from MYs 2017-2020, which is the first cost model year in the Scenarios Input File. NHTSA calculates the final unit DMC for AC efficiency technologies to be \$14.55 per gram of CO₂/mile for passenger cars and light trucks, in 2021\$ in MY 2020. Finally, NHTSA uses GDP Price Deflators to convert the unit DMC to 2024\$, adjusted it for RPE, and applied learning factors to estimate total costs for MYs 2020-2050.⁵³³ Table 3-88 contains a summary of the AC efficiency technology credit values, unit DMCs, and MY 2020 total cost. Table 3-89 contains AC efficiency technology total costs for MYs 2024-2027.

Table 3-88: 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 [2024\$ / g CO ₂ /mi] in MY 2020
AC Efficiency	\$77.30	5.0	\$15.46	\$14.55	\$24.71

In its 2016 Proposed Determination TSD, EPA estimated that the off-cycle technology level 2 package, which contains 3.0 grams of CO₂/mile, would have a unit DMC of \$55.00 per gram CO₂/mile (in 2013\$) for passenger cars and light trucks in MY 2017.⁵³⁴ NHTSA uses a GDP Price Deflator to convert the original unit DMC from 2013\$ to 2021\$. NHTSA calculates the unit DMC for off-cycle technologies to be \$64.14 per gram CO₂/mile for passenger cars and light trucks, in 2021\$ in MY 2017.

Next, NHTSA applies a learning factor of 0.94⁵³⁵ to the off-cycle technology unit DMCs to translate them from MYs 2017-2020, which is the first model year in the analysis. NHTSA calculates the final unit DMC (in 2021\$) for off-cycle technologies to be \$55.99 per gram of CO₂/mile for passenger cars and light trucks in MY 2020. Finally, NHTSA uses GDP Price Deflators to convert the unit DMC to 2024\$, adjusted it for RPE, and applies learning factors to estimate total costs for MYs 2020-2050.⁵³⁶ Table 3-89 contains a summary of the off-cycle technology credit value, unit DMCs, and MY 2020 total cost. Table 3-90 contains off-cycle technology total costs for MYs 2024-2031. For this analysis, these costs run through MY 2031 for the No-Action Alternative and NHTSA cuts out the costs after MY 2027 in the action alternative.

Table 3-89: 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 [2024\$ / g CO ₂ /mi] in MY 2020
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⁵³² The learning factor for AC efficiency technologies in MY 2020 is 0.94, which was in the 2020 final rule for MYs 2021-2026.

⁵³³ Though the final model year in the study period is MY 2050, the final model year in the Scenarios Input File in MY 2040. The Model assumes the total costs for AC efficiency and off-cycle technologies remain constant from MYs 2041-2050.

⁵³⁴ EPA, Midterm Evaluation of Light-Duty Vehicle Greenhouse Gas Emissions Standards for Model Years 2022-2025, last revised: May 15, 2025, available at: <https://www.epa.gov/regulations-emissions-vehicles-and-engines/midterm-evaluation-light-duty-vehicle-greenhouse-gas> (accessed: May 25, 2026).

⁵³⁵ The learning factor for AC efficiency technologies in MY 2020 is 0.94, which was in the 2020 final rule for MYs 2021-2026.

⁵³⁶ Though the final model year in the study period is MY 2050, the final model year in the Scenarios Input File in MY 2040. The Model assumes the total costs for AC efficiency and off-cycle technologies remain constant from MYs 2041-2050.

Off-Cycle	3.0	\$55.00	\$64.14	\$59.99	\$101.96
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Table 3-90: AC Efficiency and Off-Cycle Technology Total Costs in 2024\$ per Gram of CO₂ per Mile

Reg Class	Technology	2024	2025	2026	2027	2028	2029	2030	2031
Passenger Car	AC Efficiency	\$22.79	\$22.33	\$21.88	\$21.45	\$21.02	\$20.60	\$20.19	\$19.78
	Off-Cycle	\$95.54	\$94.26	\$92.85	\$91.45	\$90.08	\$88.73	\$87.40	\$86.09
Light Truck	AC Efficiency	\$22.79	\$22.33	\$21.88	\$21.45	\$21.02	\$20.60	\$20.19	\$19.78
	Off-Cycle	\$95.54	\$94.26	\$92.85	\$91.45	\$90.08	\$88.73	\$87.40	\$86.09

4. Consumer Response to Manufacturer Compliance Strategies

4.1. Macroeconomic Assumptions that Affect and Describe Consumer Behavior

NHTSA relies on projections of future fuel prices to evaluate manufacturers’ use of fuel-saving technologies, the resulting changes in fuel consumption, and various other impacts. The analysis includes modules addressing consumer choices, including projecting future demand for LDV travel, sales of new vehicles, and the retirement of used vehicles under each regulatory alternative. Constructing these forecasts requires projections of macroeconomic and demographic variables, including U.S. GDP and Personal Disposable Income, consumer confidence, and U.S. population and household formation.

4.1.1. Gross Domestic Product and Other Macroeconomic Assumptions

NHTSA employs projections of future fuel prices from the EIA’s 2026 AEO.⁵³⁷ EIA uses its NEMS in conjunction with forecasts of selected macroeconomic variables obtained from S&P Global Market Intelligence U.S. Macroeconomic Outlook to produce the AEO, which presents projections of future fuel prices, among many other energy-related variables. AEO projections of energy prices and other variables are not predictions of what will happen; rather, they are projections of the likely future course of these variables that reflect their past relationships, specific assumptions about future developments in global energy markets under different macroeconomic and policy scenarios, and the forecasting methodologies incorporated in NEMS.

For projections related to fuel prices and fleet shares of gas-powered vehicles, NHTSA uses the “Alternative Transportation and Electricity” case from the 2026 AEO. The 2026 AEO “Counterfactual Baseline” case includes several policies that have subsequently changed, including Federal emission standards for light-duty vehicles and power plants.⁵³⁸ The Alternative Transportation and Electricity case better encapsulates these changes in policies and, therefore, is more representative of economic conditions moving forward.

NHTSA’s CAFE Model also relies on S&P’s Global Market Intelligence U.S. Macroeconomic Outlook for forecasts of real GDP, real disposable personal income, U.S. population and number of households, and the University of Michigan Index of Consumer Sentiment to project new vehicle sales in future model years and retirement rates for used vehicles.⁵³⁹ Because EIA relies on that same source for forecasts of these macroeconomic variables to develop the energy demand projections in AEO, the fuel and electricity

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
- Technologies Input File
- Market Data Input File

⁵³⁷ Data from the 2026 AEO can be accessed at https://www.eia.gov/outlooks/aeo/tables_ref.php.

⁵³⁸ For a complete discussion of the policies included in the 2026 AEO Counterfactual Baseline case and the alternative case used in this rule, see https://www.eia.gov/outlooks/aeo/assumptions/pdf/Legs_Regs_2026.pdf.

⁵³⁹ S&P’s US Macro Model data are available on a fee basis at <https://www.spglobal.com/market-intelligence/en/solutions/products/us-economic-modeling-forecasting-services#macro>.

price projections NHTSA obtains from EIA are consistent with the S&P economic forecasts.⁵⁴⁰ For example, the EIA 2026 AEO projections for fuel prices relies on data from the Fall 2025 S&P Macroeconomic Outlook. NHTSA updates the projections of consumer sentiment used in the CAFE Model with the Fall 2025 S&P forecast. While the Spring 2026 version 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 2026 AEO. As a result, using the Fall 2025 projections produce a more 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 (Thousands)	Consumer Sentiment	U.S. Population (Millions)	Real Disposable Personal Income (Billion \$2012)
2024	23,893	132,216	72.50	340.10	16,515
2025	24,411	130,729	60.70	341.75	16,820
2026	25,056	132,095	65.39	343.01	17,419
2027	25,527	133,496	67.04	344.24	17,966
2028	25,853	134,873	72.52	345.61	18,431
2029	26,251	136,249	75.00	347.09	18,891
2030	26,711	137,610	76.08	348.50	19,349
2031	27,159	138,977	77.26	349.85	19,798
2032	27,669	140,345	77.87	351.13	20,251
2033	28,209	141,692	78.73	352.35	20,708
2034	28,782	142,999	79.71	353.53	21,225
2035	29,395	144,280	80.41	354.64	21,759
2036	29,912	145,526	80.96	355.69	22,281
2037	30,429	146,710	80.88	356.69	22,823
2038	30,948	147,843	80.24	357.62	23,375
2039	31,457	148,917	79.54	358.50	23,908
2040	31,970	149,946	78.99	359.32	24,349
2041	32,468	150,924	78.24	360.07	24,839
2042	32,983	151,870	78.08	360.77	25,344
2043	33,513	152,783	78.14	361.41	25,866
2044	34,049	153,677	78.47	362.00	26,393
2045	34,588	154,576	78.64	362.54	26,824
2046	35,114	155,480	78.77	363.05	27,344

⁵⁴⁰ EIA uses S&P Global’s U.S. 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 U.S. model.

2047	35,619	156,380	78.91	363.51	27,872
2048	36,121	157,277	79.09	363.94	28,414
2049	36,612	158,173	79.33	364.35	28,968
2050	37,118	159,073	79.58	364.73	29,542

During the remainder of the second half of the 2020s, income and GDP growth are expected to remain stable, averaging around 2 percent per year. Consumer sentiment is expected to increase slightly over the second half of the 2020s and remain stable in the long term. The U.S. population and the number of U.S. households are projected to approach slightly lower levels over the long term than previously projected.

Some relevant factors were not fully captured in the projections NHTSA used for this analysis. For example, some provisions related to OB3 are expected to affect macroeconomic growth in the near- and medium-term but were not modeled as part of the AEO projections used in NHTSA’s analysis. EIA did not explicitly model these provisions because either: (1) guidance was not yet available on how Federal agencies will implement the provisions, (2) the provisions require significant modifications to NEMS that were not possible in the time available before release of the 2026 AEO, or (3) the provisions did not align with NEMS’ analytic resolution. A detailed description of the provisions included or not included from OB3 is available from the EIA.⁵⁴¹ In addition, international petroleum markets have experienced significant volatility in the first half of 2026, after EIA had completed its AEO 2026 analysis. In the proposal NHTSA relied on a macroeconomic forecast released prior to significant changes in U.S. tariff policies and the passage of OB3 (Pub. L. 119-21). NHTSA included sensitivity cases which used more recent forecasts that incorporated the effects of these policies in order to measure some of the potential effects of these policies on its analysis. For this final rule, NHTSA’s macroeconomic forecast includes these policy changes, so the agency does not have sensitivity cases that are meant to measure their separate effects. NHTSA still analyzes sensitivity cases using updated data from S&P Global Insight’s Spring 2026 projection and EIA’s Short-term Energy Outlook to examine the impact of recent events that occurred after the release of the Fall 2025 forecast, including fuel price volatility. Results from the sensitivity analysis are included in FRIA Chapter 9.

The first year simulated in the analysis is 2025, and the agency relies on observational data (rather than forecasts) for 2024 to the greatest extent possible. New vehicle sales and used vehicle retirement rates rely most heavily on macroeconomic inputs reflect projections of the economy’s steady progress toward long-run growth amid an evolving policy landscape.

4.1.2. Fuel Prices

Fuel prices influence consumers’ demand for fuel economy. The fuel savings caused by the CAFE standards are driven by the relative effectiveness of competing fuel-economy technologies, and the total miles traveled by the LDV fleet. In the analysis, NHTSA uses the AEO 2026 Alternative Transportation and Electricity case to update the fuel price projection. The 2026 AEO “Counterfactual Baseline” includes several policies in place in December 2025 that have subsequently changed.⁵⁴² Because the Alternative Transportation case better encapsulates these changes in policies, its projections are more likely to represent economic conditions moving forward. Fuel prices are one of the least certain inputs to the analysis, particularly over the extended lifetimes of the vehicles affected by this rulemaking.

⁵⁴¹ See “AEO2026: One Big Beautiful Bill Act Assumptions in the Counterfactual Baseline and core side cases” Apr., 2026, available at: https://www.eia.gov/outlooks/aeo/pdf/2026/OBBBA_Assumptions.pdf (accessed: May 13, 2026).

⁵⁴² For a complete discussion of the policies included in the 2026 AEO Counterfactual Baseline case and the alternative case used in this rule, see https://www.eia.gov/outlooks/aeo/assumptions/pdf/Legs_Regs_2026.pdf (accessed: June 2, 2026).

In CAFE rulemakings over the last two decades, NHTSA’s forecasts of 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 consistently overestimated actual prices in the long run while sometimes under-estimating prices in the near-term. Overestimating the price of fuel has made improvements to fuel economy appear more beneficial to buyers than they have ultimately proven to be. As one illustration, the forecast used in the 2022 final rule predicted relatively low gas prices and did not anticipate the sharp rebound in prices in 2022. Gas prices eventually declined to levels closer to earlier pre-pandemic forecasts. Overall, the results of CAFE analyses are vulnerable to uncertainty about fuel prices in both directions.

EIA regularly produces a retrospective analysis that compares its previous fuel price projections to actual realized prices as a tool to inform discussions about its modeling.⁵⁴³ The Congressional Budget Office compares the performance of various oil price forecasts and found, unsurprisingly, that most forecasts perform better over shorter periods of time.⁵⁴⁴ In addition, NHTSA finds that assuming a fixed real price performs as well at predicting future prices as EIA’s projections. However, the CAFE analysis requires fuel price projections spanning several decades, and EIA is recognized as an authoritative source for projections of future developments in energy markets. Though NHTSA continues to use EIA’s projections in the analysis, the agency recognizes that future fuel prices may differ from those assumed here and addresses this possibility in the sensitivity analysis.

⁵⁴³ The most recent EIA retrospective analysis is available at <https://www.eia.gov/outlooks/aeo/retrospective/pdf/retrospective.pdf> (accessed: June 2, 2026).

⁵⁴⁴ Gecan, R., CBO’s Oil Price Forecasting Record, Working Paper 2020-03, Congressional Budget Office: Washington, D.C. (2020), available at: <https://www.cbo.gov/publication/56356> (accessed: May 22, 2026).

Figure 4-1: Real Gasoline Price Forecasts in CAFE Rulemakings and Observed Prices⁵⁴⁵

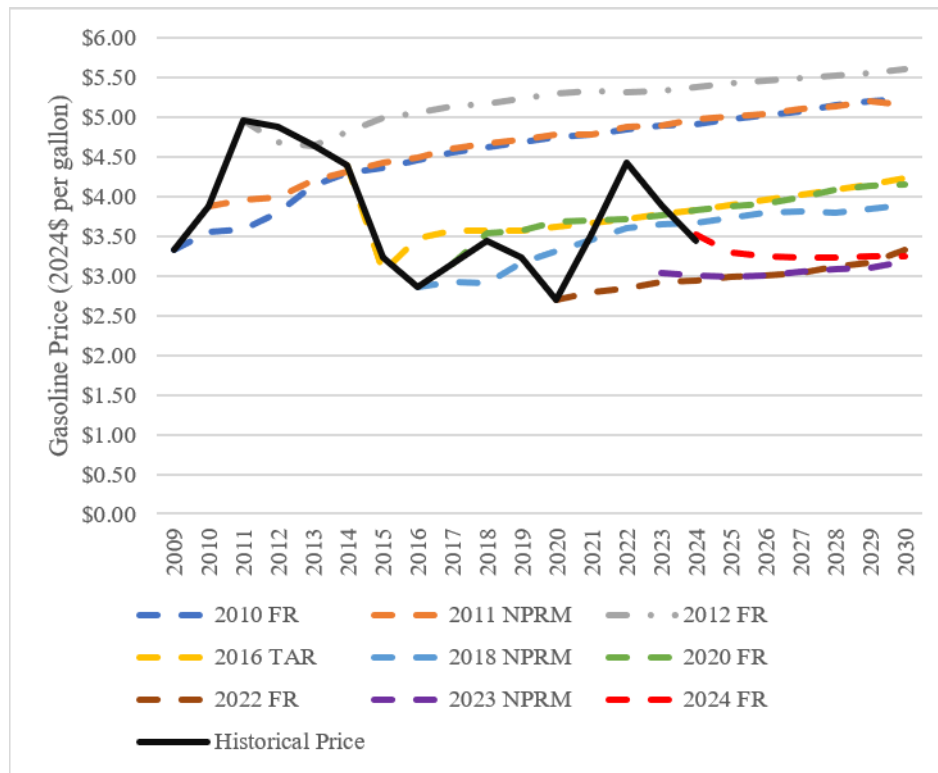
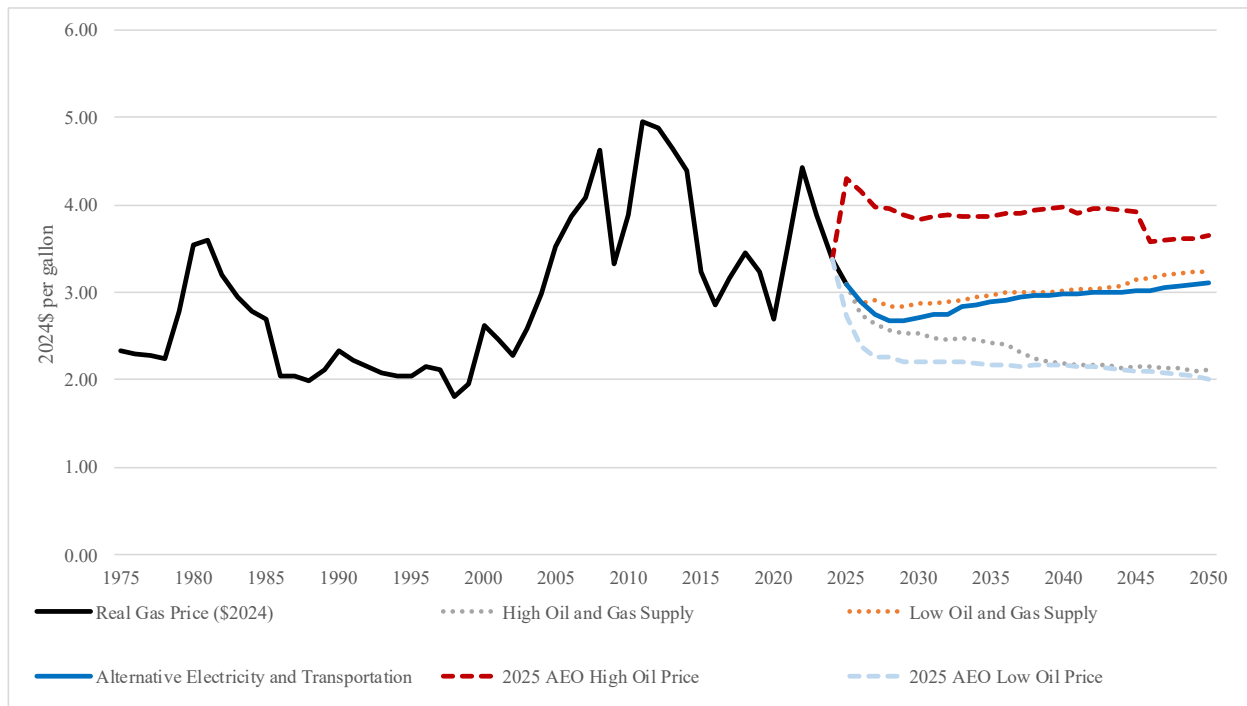


Figure 4-2 displays the High Oil and Gas Supply, Low Oil and Gas Supply, and Alternative Transportation and Electricity case gasoline price projections from AEO 2026 alongside historical, real gasoline prices dating back to the inception of the CAFE program. The figure also shows the High Oil Price, and Low Oil Price cases from the 2025 AEO.⁵⁴⁶

⁵⁴⁵ Real prices are expressed in 2024 dollars. Historical price for gasoline is taken from EIA.

⁵⁴⁶ The 2026 AEO did not include the High Oil Price and Low Oil Price cases.

Figure 4-2: Real Fuel Price Assumptions in Historical Context



These projections allow NHTSA to examine extreme cases with higher or lower prices over both the short and long term. Table 4-2 shows projections from each of these AEO forecasts for 2026-2027, alongside the May 2026 EIA Short-term Energy Outlook (STEO) forecast. The STEO forecast for gasoline prices exceeds both the Alternative Electricity and Transportation case and the Low Oil and Gas Supply case forecasts, but is still below the forecast from the High Oil Price case in the 2025 AEO. As a result, NHTSA’s sensitivity analysis captures the full range of possible outcomes related to future fuel prices, including recent price volatility.

Table 4-2: Projections for Gasoline Prices, 2026-2027 (\$2024 per-gallon)

Projection	2026	2027
2026 AEO		
- Alternative Electricity and Transportation	2.89	2.74
- Low Oil and Gas Supply	2.88	2.91
- High Oil and Gas Supply	2.74	2.65
2025 AEO		
- High Oil Price	4.16	3.98
- Low Oil Price	2.38	2.26
May 2026 STEO	3.76	3.51

The central analysis uses the AEO 2026 Alternative Transportation and Electricity case fuel price projections. The other series shown here are used to develop bounding cases for the sensitivity analysis. The purpose of the analysis of these sensitivity cases is to measure the degree to which important projected outcomes could change under different assumptions about fuel prices. These sensitivity cases do not posit a more credible future state of the world than the reference baseline. NHTSA assumes the Alternative Transportation and Electricity case is the most likely future state. FRIA Chapter 9 discusses the sensitivity analysis further.

4.2. Fleet Composition

The size and composition of the on-road fleet is a critical element of NHTSA’s analysis of CAFE standards. The costs of more expensive technology added by manufacturers when needed to meet CAFE standards influence the sticker and actual selling prices of new vehicles, and consumers may respond by changing the type or specific model of the new vehicle they buy or by purchasing a used vehicle. These decisions affect how long older vehicles remain in the fleet, and how many miles are driven in total by new and used vehicles of different ages. Each model year cohort of the fleet is simulated dynamically within the CAFE Model, and its evolution over time responds to regulatory alternatives, fuel prices, tax incentives, and macroeconomic conditions that affect its remaining size, composition, and usage.

The following subchapters discuss how new vehicle sales of cars and light trucks—the annual addition of new vehicles to the fleet or registered population—would likely evolve over future model years in response to the different levels of CAFE standards analyzed in the final rule. The discussion considers the influence of increasing durability of new vehicles and of changing economic conditions on the rate at which used vehicles of different model year cohorts and ages are retired from service under the No-Action Alternative. The discussion identifies 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., NHTSA has been unable to develop a single model that accounts for interactions between the new and used vehicles markets. NHTSA believes its current approach reasonably captures the sources of changes in fleet composition that are attributable to changing CAFE standards and allows policy-makers to make informed opinions about the consequences of alternative stringency levels.

4.2.1. Changes in New Vehicle Sales

The CAFE Model assumes 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.⁵⁴⁷ Manufacturers’ added costs to employ technologies that reduce fuel consumption increase new vehicle prices, while those technologies generate a stream of future fuel savings. Evidence from academic literature suggests that higher new vehicle prices resulting from stricter CAFE standards suppress sales.

To isolate the impact of these standards, the CAFE Model breaks the sales response module into three discrete components. The first component predicts the evolution of the overall size of the LD fleet under the reference baseline conditions, which include prevailing CAFE standards and forecasts of demographic and macroeconomic growth. This component uses a projection of ICE vehicle market share from the 2026 AEO to predict the No-Action overall sales volumes for future years.

The second component measures how the combination of changes in new vehicle prices, tax incentives earned, and fuel-economy levels contributes to differences in sales among regulatory alternatives. By modeling sales in the first component as a function of macroeconomic conditions and then applying an independent own-price elasticity to estimate the change in sales across alternatives, the CAFE Model is able to distinguish between sales expected in future years under those reference baseline conditions and incremental changes in sales from their reference baseline level under each alternative. The third component determines how market shares of light trucks and passenger cars in the LD fleet are likely to

⁵⁴⁷ The question of cost pass-through is one that academic and industry researchers have considered for decades. NHTSA explores some of these theories in FRIA Chapter 7.1.

evolve under reference baseline conditions, and how changes in their relative prices among regulatory alternatives are likely to affect those shares.⁵⁴⁸

4.2.1.1. How NHTSA Models Consumer Willingness to Pay for Fuel Savings

To model changes in new vehicle sales in response to fuel economy standards, NHTSA accounts for two effects: (1) higher fuel-economy-technology levels increase the cost of producing vehicles and thus their selling prices, while (2) reduced fuel costs make fuel-efficient vehicles more attractive to consumers and increase demand. To estimate the impact of the rule on new vehicle sales, NHTSA must make some assumptions about consumers' WTP for future fuel savings, and thus how much the required increase in fuel economy increases their value to potential buyers.

Chapter 2 of the FRIA contains a discussion of consumers' WTP for improved fuel economy, including a discussion of underlying theories of how consumers behave, a literature review, and empirical estimates from the literature on consumers' valuation of fuel savings over vehicles' lifetimes. In FRIA Chapter 2, NHTSA analyzes sacrifices in other vehicle attributes as the likeliest explanation for consumers' apparent unwillingness to pay higher prices to purchase models that would repay their price premiums (in present value terms) via the fuel savings they offer over their expected lifetimes. NHTSA discusses these sacrifices in greater detail in Chapter 6.1.3.

In prior rulemakings, NHTSA assumed that potential buyers value fuel savings from buying a higher mpg model equivalent to the savings they realize 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 assumption was based on what manufacturers communicated to the agency in the past about how they believed buyers value future fuel savings.

The economics literature shows a wide range of estimates for how much consumers appear to value fuel savings. Table 4-3 presents results from a meta-analysis of estimates from the literature taken from Greene (2018). Results indicate that the methodology and data used to produce the estimate play a significant role, as estimates taken from stated preference surveys tend to indicate close to, or even more than full valuation, while other estimates tend to hover closer to 50-60 percent on average. The full set of results indicate a range between 55-93 percent, with a mean of 74 percent.

Table 4-3: Meta-Analysis of Estimates of Willingness to Pay for Fuel Cost Savings (Greene, 2018), Expressed as a Percentage of Lifetime Fuel Savings⁵⁴⁹

Data Type	Mean	95% Conditional Confidence Interval - Low	95% Conditional Confidence Interval - High
Market Sales	59%	29%	89%
Revealed Preferences Survey	48%	28%	67%
Stated Preferences Survey	107%	82%	131%
Market Sales + Revealed Preferences	60%	39%	82%

⁵⁴⁸ The reference baseline uses the existing model level classification for vehicles in the fleet between passenger cars and light trucks. NHTSA's methodology for determining class shares under the final reclassification is discussed in Final TSD Chapter 4.2.1.3.

⁵⁴⁹ Estimates taken from Greene, D. *et al.*, Consumer Willingness to Pay for Vehicle Attributes: What Do We Know? Transportation Research Part A: Policy and Practice vol 118(c): pp. 258–279 (2018). Percentage of lifetime fuel savings is computed consistent with the assumptions outlined by the authors. These include 115,000 miles of discounted lifetime travel at 6 percent private discount rate. Valuation is expressed in 2015\$ that buyers were willing to pay for a 1 cent (2015) per-mile improvement in costs. Estimates are limited to fixed coefficient models. Random coefficient model results come from a comparatively smaller set of papers (27 vs. 68), and show unreasonable results (for example market sales results produce a negative value, while survey results show valuation of several times the value of lifetime fuel savings). For this reason they were not included in this table.

All Estimates	74%	55%	93%
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NHTSA also examined more recent empirical economics literature for evidence to inform a consumer valuation assumption, and the agency’s survey of that research is summarized in Table 4-4. The evidence likewise suggests a wide range for how much buyers are likely to value savings in fuel costs. While some recent papers indicate valuation well below 50 percent, their central tendency is between 50-60 percent, with significant variation on either side, including up to full-lifetime savings. Overall, this smaller sample of more recent papers appears broadly consistent with findings from earlier literature based on revealed preference and market sales-based studies.

Table 4-4: Payback Periods Implied by Recent Research on Car Buyers’ Behavior⁵⁵⁰

Author(s) (Publication Date)	Scope	Approximate Equivalent Payback Period (months)	Percent of Lifetime Fuel Cost Savings
Greene, Evans, and Hiestand (2013) ⁵⁵¹	Interviews of new car shoppers and buyers	24-36 months*	
Allcott and Wozny (2014) ⁵⁵²	Used cars	60 months [#]	45% (at 3% DR)
Busse, Knittel, and Zettelmayer (2013) ⁵⁵³	New cars	120 months to > full-vehicle lifetime [#]	54%-87% (at 3% DR)
	Used cars	72 months [#]	
Sallee, West, and Fan (2016) ⁵⁵⁴	New and used vehicles	> Full-vehicle lifetime*	101% (at 5% DR)
Leard (2018) ⁵⁵⁵	New vehicles	48 months [#]	45%
Gillingham, Houde, and Van Bentham (2021) ⁵⁵⁶	New vehicles	18-48 months [#]	16%-39% (at 4% DR)
Leard, Linn, and Zhou (2023) ⁵⁵⁷	New vehicles	72 months [#]	69% (at 5% DR)

⁵⁵⁰ Some survey data such as Consumer Reports show consumers with lower payback periods (around 24 months). However, the methodology employed by surveys like Consumer Reports is less rigorous than the revealed preferences data from the other sources, which is why OMB Circular A-4 directs agencies to attempt to use studies that rely on revealed preferences when feasible.

⁵⁵¹ Greene, D. *et al.*, Survey Evidence on the Willingness of U.S. Consumers to Pay for Automotive Fuel Economy, *Energy Policy*, Vol. 61: pp. 1539 – 50 (2013), available at: <https://doi.org/10.1016/j.enpol.2013.05.050> (accessed: May 22, 2026).

⁵⁵² Allcott, H., & Wozny, N., Gasoline Prices, Fuel Economy, and the Energy Paradox, *The Review of Economics and Statistics*, Vol. 96(5): pp. 779 – 95 (2014), available at: https://doi.org/10.1162/REST_a_00419 (accessed: May 22, 2026).

⁵⁵³ Busse, M. *et al.*, Are Consumers Myopic? Evidence from New and Used Car Purchases, *American Economic Review*, Vol. 103(1): pp. 220 – 56 (2013), available at: <https://hdl.handle.net/1721.1/87769> (accessed: May 22, 2026).

⁵⁵⁴ Sallee, J. *et al.*, Do Consumers Recognize the Value of Fuel Economy? Evidence from Used Car Prices and Gasoline Price Fluctuations, *Journal of Public Economics*, Vol. 135: pp. 61 – 73 (2016), available at: <https://www.nber.org/papers/w21441> (accessed: May 22, 2026).

⁵⁵⁵ Leard, B., Consumer Inattention and the Demand for Vehicle Fuel Cost Savings, *Journal of Choice Modeling*, Vol. 29: pp. 1 – 16 (2018), available at: <https://doi.org/10.1016/j.jocm.2018.08.002> (accessed: May 22, 2026).

⁵⁵⁶ Gillingman, K., *et al.*, Consumer Myopia in Vehicle Purchases: Evidence from a Natural Experiment, *American Economic Journal*, 13(3): pp. 207-238 (2021).

⁵⁵⁷ Appendix of Leard, B. *et al.*, How Much Do Consumers Value Fuel Economy and Performance? Evidence from Technology Adoption, *The Review of Economics and Statistics*, Vol. 105(1): pp. 158 – 174 (2023), available at: https://doi.org/10.1162/rest_a_01045 (accessed: May 22, 2026).

Leard, Linn, and Springel (2023) ⁵⁵⁸	New vehicles	36 months*	22% (demographic group specific rates)
*Reported by author(s). # Estimated by NHTSA staff using current CAFE Model data on mileage accumulation and survival probability by vehicle age; assumes buyers do not discount future fuel savings. When ranges of estimates are reported in a study, NHTSA staff included the midpoint of the range in the table above.			

Most of these estimates rely on variation in vehicles’ selling prices that are attributable to differences in their expected future fuel costs, which in turn stem from the differential effect of changes in fuel prices on per-mile fuel costs for vehicles with varying fuel-economy levels (as well as on expected future fuel prices). This approach enables researchers to use detailed descriptions of vehicle models to control for differences in their other features.⁵⁵⁹ These controls not only provide more accurate estimates of the WTP for fuel savings, but also intentionally limit the variation in other features that NHTSA concludes are responsible for payback periods shorter than the full lifetime of the vehicle. Because these other factors are relevant in explaining buyer behavior, these estimates are less suitable for defining the payback period used in the CAFE Model.

In addition to reconsidering academic research on the topic, NHTSA examined the agency’s historical 30-month assumption by comparing past predictions of technology adoption by the CAFE Model with subsequently observed technology use. To conduct this analysis NHTSA grouped technologies into 21 groups based on groupings used in the Technologies Input File, and compared observed 2024 penetration rates to predicted rates using five different payback period assumptions (0 months, 24 months, 30 months, 36 months, 60 months).⁵⁶⁰ Predictions of the technology penetration rates were taken from the 2024 final rule which modeled technology adoption from a base MY 2022 fleet

NHTSA first examined the entire fleet at a manufacturer-regulatory class observation level. NHTSA determined the mean-squared prediction error for each manufacturer fleet. Because penetration rates vary widely across these technology groups, NHTSA normalized these errors by ranking each payback period from lowest mean-squared error to highest. This allows for a comparison of the relative performance for each payback period. NHTSA then produced three measures of the overall performance of the payback periods, as shown in Table 4-5. Looking first at average rank, it appears that payback periods of 0 to 36 months perform at relatively similar levels, while a longer 60-month payback period performs worst, and 36 months performs best, though only by a relatively narrow margin. NHTSA next examined which payback periods produced one of the worst two rates of prediction error, and which payback period produced one of the best two rates in each technology set.⁵⁶¹ The longer payback period generates a

⁵⁵⁸ Leard, B. *et al.*, Vehicle Attribute Tradeoffs and the Distributional Effects of U.S. Fuel Economy and Greenhouse Gas Emissions Standards, RFF Working Paper 23-04, Resources for the Future: Washington, D.C. (2023), available at: https://media.rff.org/documents/WP_23-04.pdf (accessed: May 22, 2026).

⁵⁵⁹ For example, Allcott and Wozny (2014) identify their estimates using variation in gasoline prices and changes in the prices of individual vehicle models, while Busse *et al.* (2013) examine variation within a given car type. Busse *et al.* (2013) define “car type” as the interaction of make, model, model year, trim level, doors, body type, displacement, cylinders, and transmission. They give the example of a 2003 Honda Accord EX four-door sedan with a four-cylinder 2.4-liter engine and automatic transmission as one such car type. Saltee *et al.* (2016) include VIN stub by month fixed effects (*e.g.*, 4-cylinder 2.0L 2005 Toyota Camry in January 2008). Leard, Linn, and Zhou (2023) include relevant performance attributes alongside fuel costs in their estimation, and include model variant fixed effects.

⁵⁶⁰ Ultimately NHTSA eliminated three of these groups due to lack of variation adoption in the fleets examined. This analysis is further described in a Docket Memo.

⁵⁶¹ NHTSA used worst and best two rather than worst and best because technology predictions were in some cases equal across multiple payback periods for technology groups, creating ties.

worst two prediction error at the highest rate, and a best two prediction error at the lowest rate, while 24- and 36- month payback periods produce the best results by these measures.

Table 4-5: NHTSA Retrospective Overall Technology Adoption Rankings Analysis, MY 2024

Modeled Payback Period	Unweighted Average Rank	Number of Times in Worst 2	Number of Times in Best 2
0 months	2.2	5	12
24 months	2.2	2	12
30 months	2.4	4	8
36 months	2.1	2	12
60 months	3.0	10	8

NHTSA then focused its analysis on the subset of manufacturers whose 2024 fleets were determined to be able to over-comply with the existing standards in 2024.⁵⁶² Between 2022 and 2024, manufacturers were subject to CAFE standards that influenced the amount of fuel economy manufacturers were applying to their fleets. To isolate the fuel-economy technology added voluntarily in response to consumer demand—rather than technology added to meet the existing standards—the agency focused its analysis on manufacturers that exceeded their CAFE targets.

Table 4-6 shows results from this analysis. The first three columns reproduce the same measures shown for the full fleet. Here the story is somewhat clearer; 36 months performs best with an average rank of two, while the more extreme payback periods (0 and 60 months) perform worst. Next NHTSA examined the number of times that each payback period ranked fourth or fifth best, and the number of times it ranked first or second best. Here, 36 months recorded the fewest low performing ranks, and tied with 30 months for the most top performing ranks.

Finally, NHTSA took a variance weighted average rank across the technology groups. Technology groups with the most variation in adopted rates were weighted more highly, while those with little variation were weighted lower. This limits the influence of technologies where penetration rates were very closely stacked, or had no variation at all, since in these cases differences across payback periods were trivial compared to other technologies. The highest weighted group of technologies using this methodology were mass reduction, while Turbo P2 showed the least variation. Here, the 36-month payback period once again performed best at an average rank of 2.3.

Table 4-6: NHTSA Retrospective Over-complier Technology Adoption Rankings Analysis, MY 2024

Modeled Payback Period	Unweighted Average Rank	Number of Times in Worst 2	Number of Times in Best 2	Variance-Weighted Average Rank
0 months	2.6	7	10	2.6
24 months	2.4	5	11	3.1
30 months	2.3	3	12	2.6
36 months	2.1	2	12	2.3
60 months	2.8	8	10	2.7

The totality of evidence indicates that 36 months performs best as a payback period modeling assumption. For this reason, NHTSA elected to adjust its payback assumption upward from 30 months to 36 months

⁵⁶² Compliance was determined using each manufacturer’s full production fleet as modeled in the EIS. Manufacturers not modeled in the 2024 final rule were not included in the sample, nor were manufacturers who produced exclusively BEVs, since technology adoption across many of the categories considered in the analysis for these manufacturers is trivial.

during the proposal and has retained that estimate for the final rule. NHTSA explores the sensitivity of its result to this change and to the payback period more broadly in FRIA Chapter 9.

NHTSA recognizes that a complete analysis would incorporate both consumers' valuation of fuel savings and any loss in WTP attributable to sacrifices in other features made by manufacturers to comply with higher standards. These would be best modeled directly. In the past, NHTSA has explored using a discrete choice model to do so, but as explained in preamble Section II.E.1, those efforts have not yet produced a satisfactory and operational model.⁵⁶³ In the absence of being able to model changes to other vehicle attributes directly, the agency must rely on another method to estimate the implicit opportunity cost (IOC). As explained in Chapter 6.1.3, resetting the standards would allow vehicle manufacturers to produce vehicles that are more attractive to buyers, leading purchasers to gain more utility from buying new vehicles. Also, consumers would be more willing to purchase vehicles with these attributes. Therefore, the agency must account for the sacrifice in other vehicle attributes by both estimating the IOC and by setting the sales payback period below the fuel savings that consumers would value absent a change in other vehicle attributes.⁵⁶⁴

Based on its analysis of the economics literature, NHTSA assumes that, in the absence of accompanying changes in vehicles' other attributes, consumers would value around 75 percent of discounted lifetime fuel savings. While the subset of more recent estimates suggests a somewhat lower average of between 50-60 percent, the range of estimates in even the more recent subset of studies is still substantial, extending to 100 percent. Thus, the 75-percent figure is consistent with the range found in the recent literature and is close to the mean of a large analysis of earlier literature found in Greene (2018). The difference between the fraction of lifetime fuel savings that consumers appear to value when vehicles' attributes remain unchanged and the fuel savings occurring within the 36-month payback period must be offset by sacrifices in vehicles' other attributes manufacturers make as part of their efforts to comply with higher fuel economy standards. This assumption and the calculation NHTSA uses to approximate the IOC are explained in further detail in Chapter 6.1.3.4.

In its sales model, NHTSA assumes that: (1) after accounting for accompanying sacrifices in other vehicle attributes, consumers are willing to pay for fuel-economy improvements that pay back within the first three years of vehicle ownership (at average usage rates); (2) manufacturers know this and provide these improvements even in the absence of regulatory pressure; (3) the amount of technology for which buyers are willing to pay rises (or falls) with rising (or falling) fuel prices; (4) consumer WTP is the same with or without higher fuel economy standards; and (5) potential buyers consider these fuel savings when evaluating the impact of new vehicle prices on vehicle purchase and retirement decisions.

The agency assumes that when accounting for accompanying sacrifices in other vehicle attributes, buyers value savings in fuel costs over only the first 36 months they own a more fuel-efficient model. This amounts to roughly one-third of its undiscounted expected lifetime savings in fuel costs, but more than half of the fuel savings over the course of the average length consumers keep new vehicles. These savings offset only a fraction of the expected increase in new vehicle prices that the agency estimates

⁵⁶³ NHTSA's experience partly reflects the fact that these models are highly sensitive to their data inputs and estimation procedures, and even versions that fit well when calibrated to data from a single period—usually a cross section of vehicles and shoppers or actual buyers—often produce unreliable forecasts for future periods, which NHTSA's regulatory analyses invariably require. This occurs because they are often unresponsive to relevant shifts in economic conditions or consumer preferences, and also because it is difficult to incorporate factors such as the introduction of new model offerings—particularly those utilizing advances in technology or vehicle design—or shifts in manufacturers' pricing strategies into their representations of choices and forecasts of future sales or market shares. For these reasons, most vehicle choice models have been better suited for analysis of the determinants of historical variation in sales patterns than for forecasting future sales, volumes, and market shares of particular categories.

⁵⁶⁴ NHTSA explored using a simple model of directly estimating the value of the IOC. NHTSA analyzed results from a sensitivity analysis using this approach in FRIA Chapter 9.

would be required for manufacturers to recover their increased costs for making the improvements to fuel economy that standards require. Under this assumption, CAFE standards cause sales of new 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 consumers value fuel savings at the time of new vehicle purchase do not apply to how NHTSA values future fuel savings in its social benefit-cost analysis. NHTSA’s benefit-cost analysis includes the full-lifetime value of fuel savings resulting from improvements to vehicles’ fuel economy, 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 and light trucks sold each year rather than the absolute number of sales under any of the alternatives. Recognizing this metric, the sales response in NHTSA’s CAFE Model includes four components: (1) a reference baseline forecast of the level of sales for each regulatory class of vehicle, based upon forecast macroeconomic inputs and external projections of changes in the market share of gas-powered vehicles; (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 LD fleet; and (4) a price-based adjustment that produces different passenger car and light truck market shares of light-duty vehicle sales under each alternative.

The structure of the sales module reflects the idea that total new vehicle sales are driven by conditions in the economy that are external to the automobile industry. New vehicle sales are highly cyclical, rising when prevailing economic conditions are positive (periods of growth) and falling during periods of economic contraction. Changes to vehicle model offerings and their features that reflect manufacturers’ compliance efforts influence the total volume of new vehicle sales, causing the marginal differences among regulatory alternatives that the sales module is designed to simulate, as rising vehicle prices generally reduce total sales.

The first component of the sales response model is the nominal forecast, which 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. This statistical model is used to project sales under the reference baseline. The reference baseline sales forecasting model does not include prices and is not intended for statistical inference about price responses in the new vehicle market. The reference baseline forecast for LDVs is derived from a statistical model (Equation 4-1 and Table 4-7 below) that includes a set of macroeconomic factors affecting new LDV sales. NHTSA uses a combination of compliance data and projections from EIA’s 2026 AEO to forecast reference baseline sales.

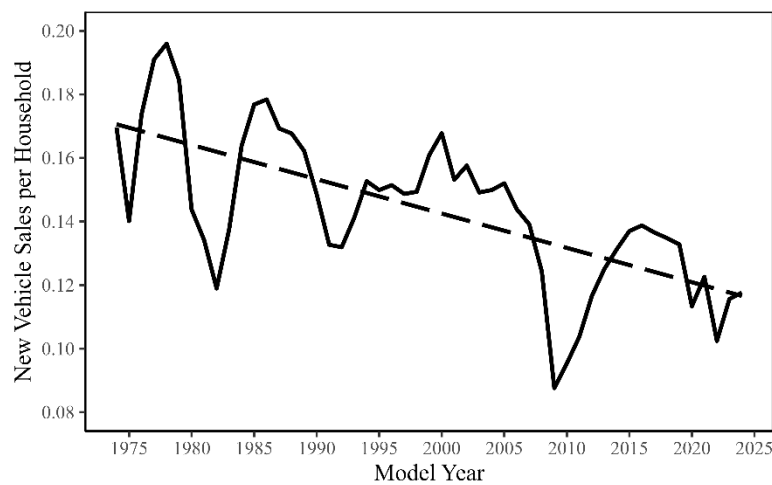
As the equation and table show, NHTSA’s LD sales model accounts for the number of households in the United States, and recent numbers of new vehicles sold, GDP, and consumer confidence. The structure of the forecast model is a time-series autoregressive distributed lag specification, a form that is widely 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.⁵⁶⁵ While this variable still exhibits the cyclical behavior that new total 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

⁵⁶⁵ U.S. Census Bureau, Total Households (2024), last revised: Nov. 12, 2024, available at: <https://fred.stlouisfed.org/series/TTLHH> (accessed: May 22, 2026).

trend over time. This is in part driven by the decline in average household size from 3 members to around 2.5 during this time period.⁵⁶⁶

Statistical testing (using the augmented Dickey-Fuller unit root test) revealed that the models' dependent variable is non-stationary,⁵⁶⁷ 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 captures the potential for some households to “overshoot” their desired vehicle ownership levels by purchasing additional cars or light trucks during periods of robust income growth but then avoiding 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).

Figure 4-3: New Light-Duty Vehicle Sales per Household in the United States, 1974-2024



The forecast model includes the natural logarithms of real U.S. GDP and consumer sentiment, as measured by the University of Michigan survey of consumers, as its primary explanatory variables. Because both series are non-stationary as well, so 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 4-7.

Equation 4-1: Statistical Model Used to Generate Nominal Forecast

$$\begin{aligned} \text{NewVehPerHH}_t &= C + \beta_1 \text{NewVehPerHH}_{t-1} + \beta_2 \text{3YrSumPerHH}_{t-1} + \beta_3 \text{LN}(\text{GDP}_t) \\ &+ \beta_4 \text{LN}(\text{GDP}_{t-1}) + \beta_5 \text{ConsumerSentiment}_t + \beta_6 \text{ConsumerSentiment}_{t-1} \end{aligned}$$

The signs of all coefficients are consistent with expectations: year-to-year 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

⁵⁶⁶ U.S. Census Bureau, Historical Households Tables (2024), available at: <https://www.census.gov/data/tables/time-series/demo/families/households.html> (accessed: May 22, 2026).

⁵⁶⁷ The series contains a unit root (*i.e.*, it is integrated of order one), based on the augmented Dickey-Fuller test.

sentiment all have statistically significant effects, while the lagged consumer sentiment variable does not. As a time series model, NHTSA considers the possibility that error terms in the Model exhibit serial correlation using a Breusch-Godfrey test. The null hypothesis of this test is that there is no first-order serial correlation in the error terms, meaning that a low p-value provides grounds to reject this hypothesis and thus is evidence of serial correlation. The p-value of the Breusch-Godfrey test for serial correlation is (0.67) at order 1, suggesting that the agency’s model is properly specified.

Table 4-7: Summary of Forecast Regression Function

Predictors	Estimates	CI	P
(Intercept)	0.14	0.06 – 0.22	0.001
NewVehPerHH _{t-1}	0.93	0.72 – 1.15	<0.001
3YrSumPerHH _{t-1}	-0.13	-0.20 – 0.06	<0.001
LN(GDP _t)	0.34	0.23 – 0.45	<0.001
LN(GDP _{t-1})	-0.35	-0.46 – -0.25	<0.001
ConsumerSentiment _t	0.0003	0.00001 – 0.0005	0.04
ConsumerSentiment _{t-1}	-0.00001	-0.0003 – 0.0003	0.93
Observations	47		
R ² / R ² adjusted	0.944 / 0.936		

Historical sales totals do not match exactly with sales totals from the compliance data used to create the CAFE Model’s 2024 fleet. This difference is 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 adjusts the intercept term in the sales model by the difference in per household sales between the two series in MY 2024. 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. NHTSA relies on projection of U.S. GDP from the 2026 AEO, and projections of consumer sentiment from the Fall 2025 S&P forecast.

While the analysis for LDVs could have relied on a forecast of new vehicle sales taken from a published source (AEO 2026 for example), using a function is an attractive option because it allows the CAFE Model to adjust the forecast dynamically in response to input changes. If a sensitivity case requires a forecast consistent with a set of specific (even if unlikely) assumptions, the Model may 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 function also allows the user to vary some of the assumptions to the analysis without creating inconsistencies with other elements of the analysis, though 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 somewhat lower than the forecast in AEO 2026’s Alternative Transportation and Electricity case, but similar in the long-term dynamics. The two forecasts, as well as the NPRM forecast are included for context in Figure 4-4. The top panel of the figure shows that both the final rule projection and 2026 AEO projection show a short-term decline in sales, followed by a significant rebound in the late 2020s,

extending to the mid-2030s, followed by a decline into the 2040s. While the level of sales is lower in the final rule projection, this is primarily a result of initial size of NHTSA’s compliance fleet. In 2024, NHTSA’s fleet was around 14.8 million vehicles, about half a million vehicles smaller than total light-duty sales from that calendar year. Figure 4-5 shows that when indexed to their 2025 levels, the final rule forecast more closely tracks the AEO forecast, though at a slight lag. Over the long term, all three forecasts reach similar levels, though the AEO and NPRM forecasts decline below initial levels in 2050, while the final rule forecast ends at a slightly higher level than in 2025.

As these forecasts illustrate, there have been significant revisions to both short-term and long-term macroeconomic expectations over the last few years. All the forecasts show that a smaller and more cautious consumer base is now expected to purchase fewer vehicles over the long term. Relative to the NPRM forecast, more recent forecasts now predict a more prolonged period of somewhat lower sales in the near term, and a later rebound in sales. As always, projections are subject to change, and NHTSA continues to update its assumptions based on the most recently published data as it becomes available. NHTSA examines how results would differ under alternative macro projections published by S&P in more recent forecasts. These results are examined in Chapter 9 of the FRIA.

**Figure 4-4: Comparison of Projected New Light-Duty Vehicle Sales with Annual Energy Outlook
Total Sales 2025-2050 (millions)**

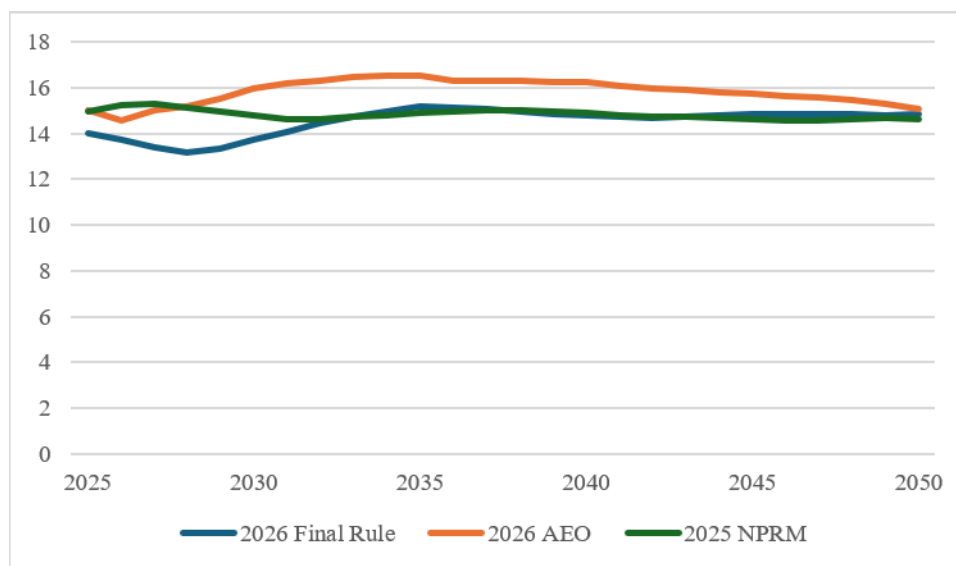
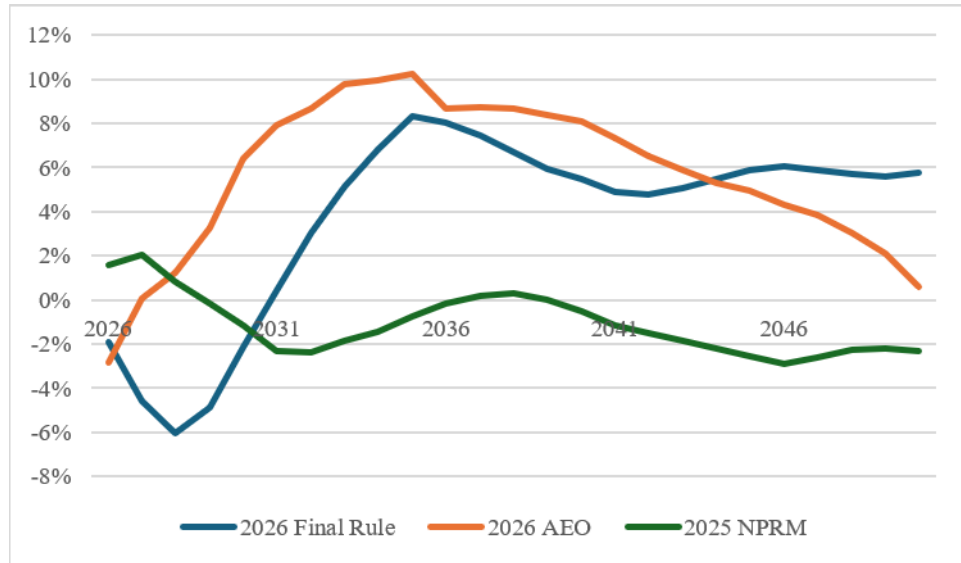


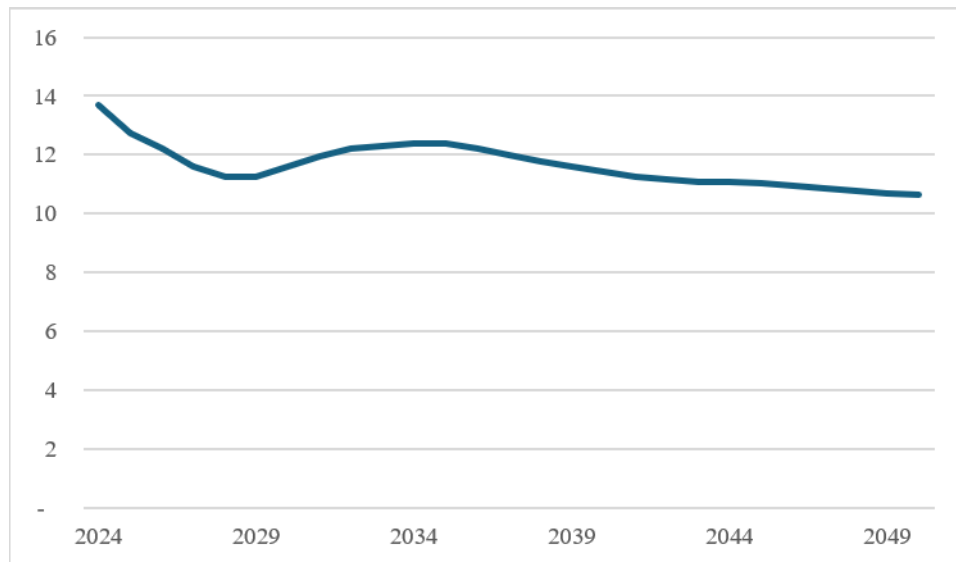
Figure 4-5: Comparison of Projected New Light-Duty Vehicle Sales with Annual Energy Outlook Percentage Growth from 2025 Levels



Because of statutory restrictions, NHTSA excludes dedicated vehicles from its analysis. NHTSA considers three methodologies for accounting for the sales for these vehicles: (1) maintaining current sales volumes in future years; (2) maintaining current market shares in future years; and (3) applying an external projection of market share for these vehicles. Ultimately, the market share of these vehicles is driven by consumer demand and manufacturers' production costs. Since neither are likely to remain at present levels over the full period NHTSA is analyzing, this conclusion indicates that the first two options are unlikely to yield accurate predictions, so NHTSA relies on the third approach. NHTSA uses the AEO 2026 Alternative Transportation and Electricity case projection for the growth rate of market shares of limited electric and fuel cell electric vehicles (FCEV) in future years.⁵⁶⁸ NHTSA applies these market shares to its total LD sales projections in order to isolate the number of gas-powered LD sales expected in future years. Figure 4-6 shows the resulting baseline sales projection for gas-powered LD sales.

⁵⁶⁸ NHTSA applied the projected year to year growth rates to its initial market shares from its 2024 Market Data Input File to project the market shares in future years.

Figure 4-6: Projected New Gas-Powered Light-Duty Sales



After forecasting the total number of new gas-powered vehicle sales for 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 on projected regulatory costs for each alternative. NHTSA elects 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 same elasticity was used in prior rules. The long-run elasticity of demand for vehicles, which tends to be much lower in magnitude than short-run elasticity, is more appropriate for analyses like this one because consumers have considerable flexibility about when to replace aging vehicles, meaning that they may delay purchases when prices increase but are likely to still purchase a vehicle eventually.

A long-run estimate is also more appropriate because it more closely matches the timeline of this final rule, in which fuel economy standards apply years into the future. Estimates of the price elasticity of new vehicle sales also need to consider interactions between the markets for new and used vehicles because the two can substitute for each other, so CAFE regulations influence prices for both. Because used vehicle prices are anticipated to increase in response to an increase in new vehicle prices and the diversion of some buyers to the used market, the change in sales in response to changes in CAFE standards is expected to be less than what would be anticipated if only new vehicle prices were affected. Recent research suggests that the measures of sales elasticity that incorporate these considerations range from -0.5 in the short-run to -0.28 in the long-run.⁵⁶⁹

The CAFE Model applies this elasticity to the difference between the alternatives' regulatory costs and the sum of the first three years' worth of fuel savings plus the value of any remaining tax credits that are passed through to the consumer. NHTSA assumes that manufacturers will pass the full costs of complying with standards onto consumers. However, any technology added to meet the standards increases 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 comply with standards, the Model includes an estimate of the partially offsetting savings in fuel costs—represented in this analysis by the 36-month WTP assumption—and its effect on demand. FRIA Chapter 7.1 contains additional information regarding the changes in supply and demand caused by the addition of technology that improves fuel

⁵⁶⁹ Jacobsen, M. *et al.*, The Effects of New-Vehicle Price Changes on New- and Used-Vehicle Markets and Scrappage, EPA: Washington, D.C. (2021), available at: https://cfpub.epa.gov/si/si_public_record_Report.cfm?Lab=OTAQ&dirEntryId=352754 (accessed: May 22, 2026).

economy. NHTSA assumes that the incidence of eligible tax credits is split evenly between consumers and manufacturers. This is discussed in greater detail in Chapter 2.5.2 and preamble Section II.C.5.

The price elasticity is applied to the percent differences in the average selling price of new vehicles between the No-Action Alternative and individual regulatory alternatives in each future year. These price differences do *not* represent increases or decreases compared to the previous year; instead, they measure the (percentage) 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 2024 (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 regulatory cost in the central analysis for the final rule includes technology costs in each affected model year.⁵⁷⁰ The change in sales for alternative a in year y relative to the reference baseline b is thus:

Equation 4-2: Calculation of Change in Sales

$$\Delta Sales_{y,a} = \frac{(\Delta RegCost_{y,a} - \Delta FuelCosts_{y,a} - \Delta TaxCredits_{y,a})}{MSRP_{2024} + RegCost_{y,b} - TaxCredits_{y,b}} \cdot PriceElasticity \cdot Sales_{y,b}$$

$\Delta RegCost$ is the difference in average regulatory cost between alternative a and the reference baseline scenario in year y , and $MSRP_{2024}$ is the average MSRP of a new vehicle in 2024. NHTSA assumes that MSRP represents the average transaction price of new vehicles in its analysis. $Sales_{y,b}$ is the forecast sales in the reference baseline in year y , $\Delta FuelCosts_{y,a}$ is the change in average fuel costs over three 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.

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 48,000 miles is assumed to be equivalent to three years of vehicle usage.⁵⁷¹

Equation 4-3: Change in Fuel Costs Used to Compute Sales Differences

$$\Delta FuelCosts_{y,a} = \left(\frac{FuelPrice_y}{NewVehFE_{y,a}} - \frac{FuelPrice_y}{NewVehFE_{y,b}} \right) * 48000$$

NHTSA assumes that consumers behave as if the fuel price prevailing when they purchase a new car or light truck is the price they face over the first three years of ownership. This means that consumers behave as if fuel prices follow a random walk, where the best prediction of (near) future prices is the current price. 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 equals 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 approach produces total sales estimates that vary among alternatives and over time. The

⁵⁷⁰ 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 36 months, the Model will apply it within the reference baseline and that cost would be incorporated into the reference baseline's regulatory cost.

⁵⁷¹ Based on odometer data, 48,000 miles is a good representation of typical new vehicle usage in the first three years of ownership and use—though the distribution of usage is large.

estimated effects on sales of the various alternatives considered here are discussed in detail in the accompanying FRIA Chapters 8.2.2 and 8.2.3.

4.2.1.3. Modeling Changes in Fleet Mix

For each alternative considered, the nominal sales forecast and price elasticity determine total industry sales in each year from 2025 to 2050.⁵⁷² The fleet share module distributes total industry LD sales between passenger cars and light trucks.

The agency follows a similar approach to the 2024 final rule and uses projections from an authoritative outside source. NHTSA had previously used parameterized functions to predict fleet shares but found that results were sensitive to small changes to its predictors and in some cases produced unrealistic results. The fleet share module relies on share projections derived from the agency's own compliance data for the 2024 fleet, and the 2026 AEO Alternative Transportation and Electricity case projections for later years.⁵⁷³ NHTSA excludes electric and FCEVs sales from the passenger car and light truck sales totals, which is used to project fleet share; NHTSA also excludes electric and FCEV sales from the compliance data, which is used to calculate the initial fleet share in 2024. To reconcile differences in the initial 2024 shares, NHTSA projects the fleet share forward using the annual changes from 2024 projected by AEO and applies these to the agency's own compliance fleet shares for MY 2024. These projected fleet shares are located in the Parameters Input File.

These shares are applied to the total industry LD 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 determined by multiplying individual manufacturers' shares of each body style (either car or light truck) by total industry sales of that body style, and assumes a manufacturer retains the same fraction of those sales as in MY 2024 for each model within that body style. This process assumes 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 MY 2024 levels.

Within a given body style, each manufacturer's shares of individual models are also assumed to be constant over time. This approach assumes 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 variable costs, and profit margins on individual vehicle models, the agency does not assume that strategic shifts within a manufacturer's portfolio occur in response to standards.

The fleet share projection NHTSA uses predicts that, in the absence of reclassification, there is a slight decline in passenger cars as a share of the gas-powered LD fleet over the long term. Between 2024 and 2050, the agency assumes in the reference baseline that passenger cars decline as a share of the fleet from just above 30 percent to about 24 percent. This represents a continuation of long-term trends, as the share of passenger cars in U.S. LDV production declines to less than half its pre-CAFE value in 1975.⁵⁷⁴ 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. In addition, passenger cars represent a significantly greater share of dedicated

⁵⁷² Sales for MY 2024 are based on totals from certified compliance data.

⁵⁷³ See EIA, AEO Table 38, Light-Duty Vehicle Sales by Technology Type, last revised: 2025, available at: <https://www.eia.gov/outlooks/aeo/data/browser/#/?id=48-AEO2025&cases=altrnp&sourcekey=0> (accessed: May 22, 2026).

⁵⁷⁴ EPA, The 2022 EPA Automotive Trends Report, Greenhouse Gas Emissions, Fuel Economy, and Technology since 1975: Executive Summary, EPA-420-R-22-029, EPA: Washington, D.C. (2022), available at: <https://www.epa.gov/system/files/documents/2022-12/420r22029.pdf> (accessed: May 22, 2026).

vehicles excluded from the analysis as compared to their broader market share, a pattern that AEO projects to continue in future years.

The projection from the 2026 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 adjusts the predicted fleet shares based on the evolving relative price difference between cars and light trucks according to their initial classification. This price change is also computed net of consumers' valuation of fuel savings and the consumer's share of any available 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 is derived from a review of the published literature and is calibrated based on estimates of own-price elasticities from the economics literature. The agency describes the calibrated logit model it uses in more detail in the memo titled "Calibrated Estimates for Projecting Light-Duty Fleet Share in the CAFE Model" found in the docket for this final rulemaking.

NHTSA selects 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 on vehicle price, which is denoted 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 represents the utility loss that the consumer experiences when prices for vehicles increase. The same coefficient on price applies in the car and light truck utility functions because decision-makers in the aggregate model are assumed to consist of all consumers. The CAFE Model uses this coefficient, the reference baseline market shares of passenger cars and light trucks, and 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

$$s_{Tti} = \frac{I}{I + e^{K_{Ct0} - K_{Tt0} + \beta(D_{Cti} - D_{Tti})}} \text{ and } s_{Cti} = \frac{I}{I + e^{K_{Tt0} - K_{Ct0} + \beta(D_{Tti} - D_{Cti})}}$$

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 to regulatory costs under each alternative, while the fuel cost measure represents savings over the first 36 months of vehicle ownership. These changes are measured for each regulatory alternative relative to the reference baseline. K_{Ct0} and K_{Tt0} are constants from the No-Action Alternative such that:

Equation 4-5: Parameterized Reference Baseline Constants

$$K_{Ct0} - K_{Tt0} = \ln\left(\frac{I}{s_{Tt0}} - I\right) \text{ and } K_{Tt0} - K_{Ct0} = \ln\left(\frac{I}{s_{Ct0}} - I\right).$$

The car share is $I - s_{Tti}$ and vice versa, ensuring that the combined fleet market shares in each alternative, at each time period, sum to 100 percent. Intuitively, β equals the percentage change in the ratio of cars to light trucks that results from an increase in the price of cars relative to light trucks. If changes to the CAFE standards cause light truck prices to increase by \$1,000 more than they cause the price of cars to increase in a regulatory alternative, the assumed value of the price coefficient suggests that the ratio of cars to light trucks should increase by 4.2 percent of the reference baseline ratio.

After determining the relative change between passenger cars and light trucks due to changes in CAFE standards, the CAFE Model reallocates vehicles between the regulatory classes based on the finalized vehicle reclassification discussed in Chapter 2.7.⁵⁷⁵ The agency determines the regulatory class of each 2024 model in the reference fleet under the finalized reclassification requirements in addition to their current compliance classification. Using initial model sales shares within each initial class and the projection of fleet shares for the initial classes described above, NHTSA allocates overall sales shares at a model level. Vehicles that are reclassified had their sales shares reallocated to their new class in the finalized model year when the new criteria would take effect. This generates an alternative set of fleet shares for the new classification under the assumption of no regulatory costs, as shown in Table 4-8.

Table 4-8: Projected Fleet Shares Under Baseline and Finalized Regulatory Classification, 2030-2050

Model Year	Prior Classification		Finalized Reclassification	
	Passenger Car	Light Truck	Passenger Car	Light Truck
2030	26%	74%	71%	29%
2031	25%	75%	71%	29%
2032	25%	75%	71%	29%
2033	25%	75%	71%	29%
2034	25%	75%	71%	29%
2035	25%	75%	71%	29%
2036	25%	75%	71%	29%
2037	25%	75%	71%	29%
2038	25%	75%	71%	29%
2039	25%	75%	71%	29%
2040	25%	75%	71%	29%
2041	25%	75%	71%	29%
2042	25%	75%	71%	29%
2043	24%	76%	70%	30%
2044	24%	76%	70%	30%
2045	24%	76%	70%	30%
2046	24%	76%	70%	30%
2047	24%	76%	70%	30%
2048	24%	76%	70%	30%
2049	24%	76%	70%	30%
2050	24%	76%	70%	30%

⁵⁷⁵ Per-vehicle costs used to determine total sales effects and fleet share effects between alternatives were determined during the compliance simulation. Since compliance by manufacturers is done using the reclassified fleet when appropriate, the per-vehicle regulatory costs account for the finalized reclassification.

This method assumes that each individual model's sales shares within the initial regulatory class remain constant. As discussed in Final TSD Chapter 3 and FRIA Chapter 6.2, the regulatory classification of a vehicle does not affect the technology applied to vehicles outside of determining which footprint curve applies, so this methodology for accounting for sales shifting does not impact the technology applied. As in the rest of the analysis, the agency does not attempt to model performance changes for existing vehicle models that may occur because of the finalized reclassification, nor does it attempt to model new vehicle lines that may be introduced into the future.

NHTSA considered applying its existing model to sales shares determined by the reclassified fleet but decided against this, because the cross-elasticities used in this analysis are estimated based on the current classification system. NHTSA also considered not adjusting fleet shares between alternatives but decided against doing so based on the importance of determining incremental costs and benefits.

4.2.2. Modeling Changes in Vehicle Retirement Rates

The effects of this rulemaking on the fuel economy, prices, and other features of new vehicles 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 vehicles affect demand for used models. In turn, this affects their market value as well as the number of used vehicles remaining in service.

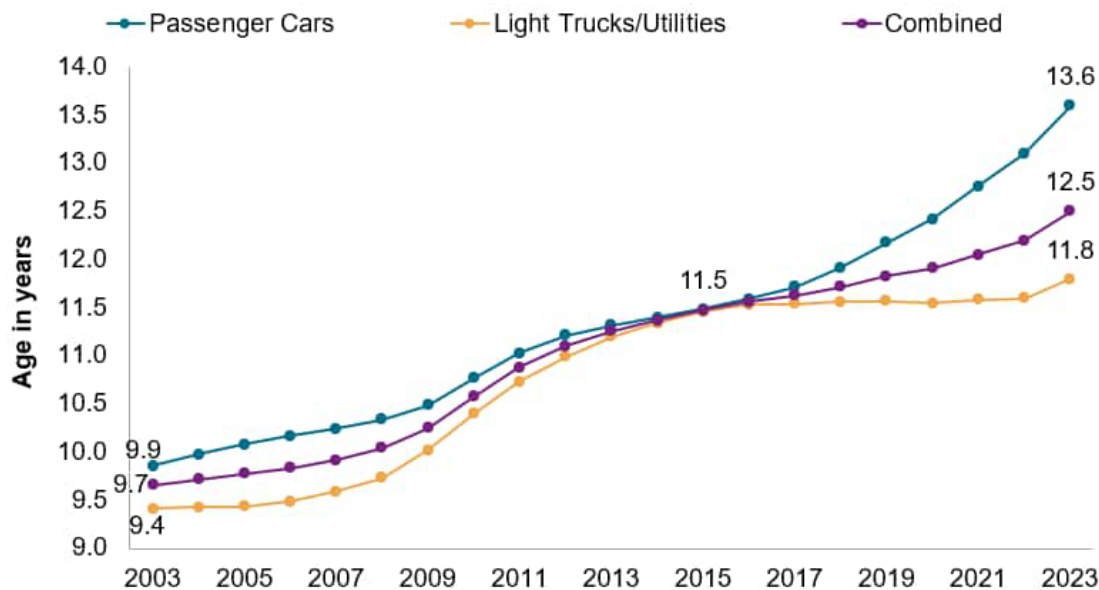
Changes in the number of used vehicles in service, and by extension how much they are driven, have important consequences for fuel consumption, emissions of pollutants, and safety. The average age of a registered LDV in the United States is rising by more than 40 percent since 1995 and topped 12.5 years for the first time in 2023 (see Figure 4-7, from S&P Global).⁵⁷⁶ In addition, differences emerge by class, with the age of passenger cars accelerating in recent years at a greater rate than light trucks, though this is also a function of declining new vehicle sales in the passenger car segment. It is important to capture the changes to vehicle usage and retirement in the used vehicle market that are potentially caused by regulation of the new vehicle market.

⁵⁷⁶ S&P Global Mobility., Average Age of Light Vehicles in the U.S. Hits Record High 12.5 years, according to S&P Global Mobility, last revised: May 15, 2023, available at: <https://www.spglobal.com/mobility/en/research-analysis/average-age-of-light-vehicles-in-the-us-hits-record-high.html> (accessed: May 22, 2026).

Figure 4-7: Average Age of a Registered Light-Duty Vehicle in United States

Average age by vehicle type

Combined average age rises for the sixth consecutive year



Source: S&P Global Mobility, U.S. average age of light vehicles as of January 1 for each year shown.
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This subchapter discusses the basis for the scrappage effect of CAFE standards for passenger cars and light trucks, traces each of these effects in detail, and explains how this effect is estimated for this final rule, which reduces CAFE standards. The magnitude of the simulated standards' effect on scrappage rates is subject to uncertainty. The agency's assumptions about how consumers value fuel economy and when manufacturers voluntarily adopt technology, the direction of the scrappage effect is unambiguous, even though the magnitude is less certain.

4.2.2.1. Foundation of the Scrappage Effect

Increased fuel economy standards increase the cost of acquiring new vehicles but also increase their fuel economy. The CAFE Model assumes that consumers value the first 36 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 36 months of fuel savings. Because the CAFE Model also assumes that in the No-Action Alternative, manufacturers will adopt fuel-economy technologies with a payback period of 36 months or less. It follows that there is likely a net price increase in any regulatory scenario that results in fuel savings greater than this period. 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,⁵⁷⁷ 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 being equal, this movement corresponds to an increase in the equilibrium price, and decrease in equilibrium quantity, of new vehicles purchased.

⁵⁷⁷ The quality-adjusted price is considered higher when regulatory compliance costs exceed 36 months of fuel savings.

New and used vehicles are substitutes. When the price of a good’s substitute increases, the demand curve for the specific good shifts outward and the equilibrium price and quantity supplied both increase. Thus, increasing the quality-adjusted price of new vehicles results in an increase in equilibrium price and quantity of used vehicles. By definition, used vehicles are not being “produced” but rather “supplied” from the existing fleet, the increase in quantity comes via a reduction in their retirement rates. 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.

FRIA Chapter 7.1 provides additional 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 (1982) shortly after the inaugural CAFE standards were promulgated in 1978.⁵⁷⁸ Gruenspecht (1982) identified criteria pollutant standards as a form of differentiated regulation, which is a regulation that affects 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 vehicles 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 in the academic literature. In preparation of the 2020 final rule—which marked the first CAFE rulemaking to model scrappage dynamically—the agency performed a detailed review of literature on this topic.⁵⁷⁹ 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 uses the literature and other regulatory scrappage models—mainly the California Air Resources Board’s (CARB) and University of California Davis Institute of Transportation Studies 2004 CARBITS vehicle transaction choice model⁵⁸⁰—as a springboard to create a scrappage model that is internally consistent with the broader CAFE Model.⁵⁸¹

While the agency did not use any particular model from the literature, the agency retained the framework outlined by Greenspan and Cohen (1999) to construct the CAFE Model’s scrappage model. Greenspan and Cohen (1999) identified two types of scrappage: engineering and cyclical scrappage.⁵⁸² Engineering scrappage represents the physical wear on vehicles that 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.

⁵⁷⁸ Gruenspecht, H., Differentiated Regulation: The Case of Auto Emissions Standards, *American Economic Review*, Vol. 72(2): pp. 328 – 31 (1982), available at: https://econpapers.repec.org/article/aeaecrev/v_3a72_3ay_3a1982_3ai_3a2_3ap_3a328-31.htm (accessed: May 22, 2026).

⁵⁷⁹ See 83 FR 43093, 43093-43094 (Aug. 24, 2018).

⁵⁸⁰ *Id.*

⁵⁸¹ There were four elements identified as being necessary. The agency noted that none of the existing scrappage models in literature met all four criteria.

⁵⁸² Greenspan, A., & Cohen, D., Motor Vehicle Stocks, Scrappage, and Sales, *Review of Economics and Statistics*, Vol. 81(3): pp. 369 – 83 (1999), available at: <https://doi.org/10.1162/003465399558300> (accessed: May 22, 2026).

In addition to allowing new vehicle prices to affect cyclical vehicle scrappage via the Gruenspecht (1982) effect, Greenspan and Cohen (1999) also noted that engineering scrappage seemed to increase when EPA criteria pollutant emissions standards became more stringent: as more costs went toward compliance technologies, scrappage increased. Greenspan and Cohen (1999) theorized two ways that fuel economy and FE standards could affect vehicle scrappage: (1) through increasing new vehicle prices, thereby increasing used vehicle prices and ultimately reducing on-road vehicle scrappage and (2) by shifting resources toward fuel-saving technologies—potentially reducing the durability of new vehicles.⁵⁸³

The current analysis uses this framework; therefore, 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 externally. The current implementation of the scrappage model is similar to the scrappage model used after the 2020 final rule, which made a variety of improvements as compared to the model used for the 2018 NPRM and addressed other substantive comments.

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 decides 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. The owner gets more value from scrapping the vehicle than continuing to drive or sell it. Typically, the owner who scraps the vehicle is not the first owner. 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 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 are removed from the fleet because of collisions or irreparable mechanical failures but they fail to appear in the registration rolls and are assumed to be scrapped.

While scrappage decisions are made at the owner level, the agency is unaware of household data sources that allow it 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*. To isolate this effect, NHTSA needs 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’s (or model year cohort’s) registration status between one period and the next. As such, the potential scrappage effect is only measured through time series data. The data contains information about national vehicle registrations in each calendar year from CYs 1975-2017.⁵⁸⁴

4.2.2.2.1.1. *Age and Durability*

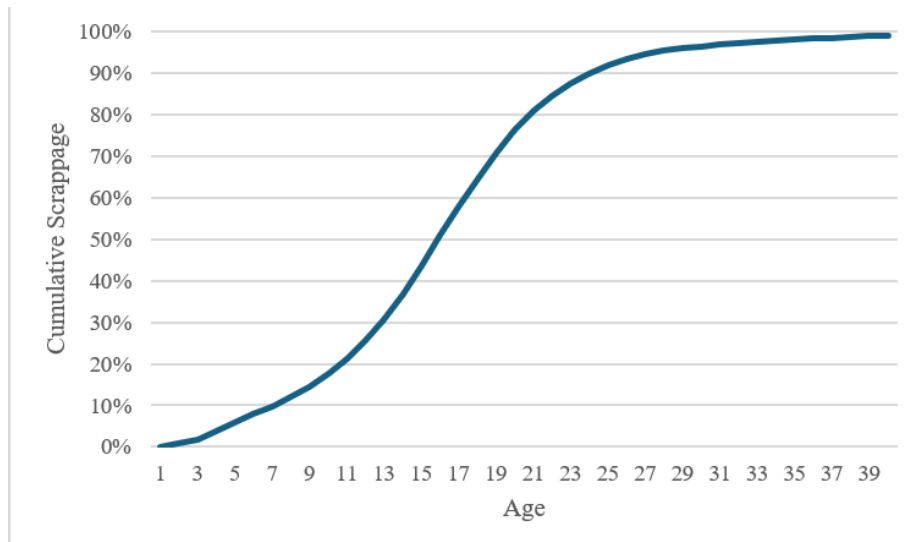
The most predictive element of a vehicle’s scrappage in a given year is the influence of “engineering scrappage.” This source of scrappage is largely determined by the age of a vehicle and the durability of a specific model year vintage. For a model year cohort, vehicle scrappage typically follows a roughly

⁵⁸³ Note that the authors posit a relationship between durability and emission standards; NHTSA does not itself have data indicating a reduction in durability.

⁵⁸⁴ The analysis begins in 1975 as this is the earliest year all required input data were available.

logistic function with age—that is, scrappage increases to some peak, and then declines with vehicle age until all (or nearly all) of the vehicles produced in a given year retire (which is illustrated in Figure 4-8).

Figure 4-8: Cumulative Scrappage for a Model Year Cohort



NHTSA uses proprietary vehicle registration data from IHS-Polk, the National Vehicle Population Profile (NVPP),⁵⁸⁵ 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 GVWR. To build scrappage models to support this final rule, it is important to aggregate these vehicle types in a way that is compatible with the existing CAFE Model.

Since 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 are 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 likely result in different lifetime scrappage patterns.

Once stratified into body style buckets, the data are aggregated into population counts by model year and age. These counts represent the population of vehicles of a given body style and model year cohort 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 model year cohort and body style from one calendar year to the next is assumed to represent the number of vehicles of that model year cohort and style scrapped in a given year.

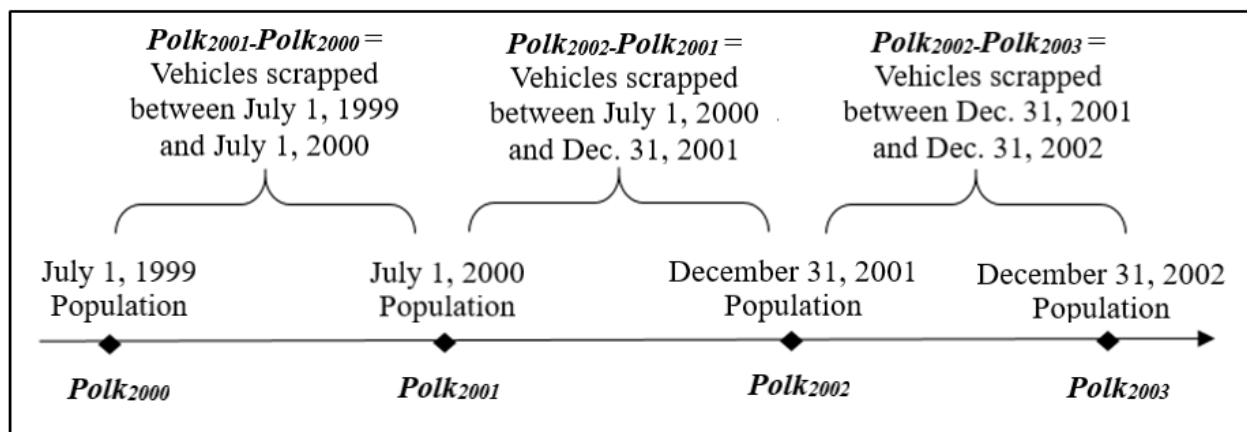
One issue with using snapshots of registration databases as the basis for computing scrappage rates is that vehicles are not removed from registration databases until the last valid registration expires. For example, if registrations are valid for a year, vehicles still appear to be registered in the calendar year in which they are scrapped. To correct for the scrappage that occurs during a calendar year, a similar correction as that used in Greenspan and Cohen (1999) is applied to the Polk registration data. NHTSA assumes that the real on-road count of vehicles of a given model year registered in a given calendar year is best represented

⁵⁸⁵ Includes content supplied by IHS Markit: Copyright © R.L. Polk & Co., 2018. All rights reserved.

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 CYs 2000-2001 remain in the Polk snapshot from CY 2000 ($Polk_{CY2000}$), as they are registered at some point in that calendar year and exist in the database. Using a simplifying assumption that all States have annual registration requirements,⁵⁸⁶ vehicles scrapped between July 1, 1999, and July 1, 2000, do not have renewed registration between July 1, 2000, and July 1, 2001, and do not show up in $Polk_{CY2001}$. The vehicles scrapped during CY 2000 are 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 is smaller than the count in the following year—not all of the model year cohort are sold and registered. For these new model years, Greenspan and Cohen (1999) assume that the Polk counts capture all vehicles present in the given calendar year and approximately one percent of those vehicles are scrapped during the year. Importantly, the analysis begins modeling the scrappage of a given model year cohort in: $CY=MY+2$,⁵⁸⁷ 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 4-9: 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.⁵⁸⁸ Scrappage computed for CY 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 1, 2000, and $Polk_{CY2002}$ represents all vehicles on the road as of December 31, 2001. For this one time period, the scrappage represents vehicles

⁵⁸⁶ 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 also would require estimates of the interstate and international migration of registered vehicles.

⁵⁸⁷ Calculating scrappage could begin at $CY=MY+1$, as for most model years, the vast majority of the fleet will have been sold by July 1 of the succeeding calendar year, but for some exceptional model years, the maximum count of vehicles for a vintage in the Polk data set occurs at age two.

⁵⁸⁸ Prior to CY 2002, Polk vehicle registration data were collected as a single snapshot on July 1 of every calendar year. For CY 2002 and beyond, Polk changed the timing of the data collection process to a rolling collection ending on December 31. That is, it considers information from other data sources to remove vehicles from the database that have been totaled in crashes before December 31 but may 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 CYs 2001-2002 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 (1999) adjustment applied does not change for the dataset compiled from Polk's new collection procedures.

scrapped over 18 months, rather than a year. For this reason, the CY 2001 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 CY 2001 is 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 causes some calendar years to contain a larger number of model year cohorts 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 4-9.

Table 4-9: 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

New and used vehicles are substitutes. Therefore, the price of new vehicles has 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).⁵⁸⁹ The transaction prices are the average amount consumers pay for new vehicles and exclude any trade-in value credited toward the purchase. The econometric model uses year-to-year variation in these prices to derive coefficients for the CAFE Model’s scrappage module. This price series captures 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. To match with simulated prices used in the CAFE Model, NHTSA adjusts prices by subtracting the average undiscounted fuel savings achieved by new vehicles in that year relative to new vehicles produced in 1975, during their first 36 months on the road. This is consistent with NHTSA’s payback period used in the rest of its analysis to simulate consumers’ valuation of fuel savings.

NHTSA did not use the New Vehicle Consumer Price Index (CPI) of the Bureau of Labor Statistics (BLS). The purpose of BLS data are to show how prices of similar goods and services change over time.

⁵⁸⁹ The data can be obtained from NADA. For reference, the data for MY 2020 may be found at: <https://www.nada.org/nada/research-data/nada-data>.

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 factors that are controlled for elsewhere in this analysis into the price calculations, making it unsuitable for this analysis.⁵⁹⁰

To ensure consistency with the sales response mechanism in the CAFE Model, the observed transaction prices are 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 36 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 are tested that allow the elasticity of scrappage to vary with age. Adjusting prices for 36 months of fuel savings represents a change in the variable construction from the estimates used in the past but is necessary to ensure consistency with the treatment of the payback period in the sales and compliance sections of the CAFE Model. Point estimates and standard errors in the results differ from those found in the 2024 final rule TSD.

Instantaneous scrappage rates are also influenced by fuel economy (FE) and fuel prices. Historical data on the fuel economy by vehicle style from MYs 1979-2016 are obtained from the 2016 EPA Fuel Economy Trends Report.⁵⁹¹ The van/SUV fuel-economy values represent a sales-weighted harmonic average of the individual body styles. Fuel prices are obtained from DOE historical values, and future fuel prices within the CAFE Model use the AEO 2025 Alternative Transportation Case fuel price projections.⁵⁹² 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.⁵⁹³ The agency expects that, as the new vehicle fleet becomes more efficient (holding all other attributes constant), 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 that the scrappage rate of vehicles from that model year should increase. It is perhaps worth noting that more efficient model year cohorts are less susceptible to changes in fuel prices, as absolute changes in their cost per mile (CPM) are smaller. The functional forms of the CPM measures are further discussed in the model specification subchapter below.

4.2.2.2.1.3. Macroeconomic Data

To capture the cyclical effects of scrappage, the Model includes 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 2026 AEO Alternative Transportation and Electricity case projection for the years CYs 2025-

⁵⁹⁰ Parks (1977) also cites a discontinuity found in the amount of quality adjustments made to the series so that more adjustments are made over time. This could further limit the ability for the BLS New Vehicle CPI to predict changes in vehicle scrappage. See Parks, R. W., Determinants of Scrapping Rates for Postwar Vintage Automobiles, *Econometrica*, Vol. 45(5): p. 1099 (1977), available at: <https://doi.org/10.2307/1914061> (accessed: May 22, 2026).

⁵⁹¹ EPA, Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 through 2016, EPA-420-R-16-010, EPA: Washington, D.C. (2016), available at: <https://19january2017snapshot.epa.gov/sites/production/files/2016-11/documents/420s16001.pdf> (accessed: May 22, 2026).

⁵⁹² Note: The central analysis uses the AEO Alternative Transportation fuel price case, but sensitivity analysis also considers the possibility of AEO's low and high fuel price cases.

⁵⁹³ Work by Jacobsen and van Benthem (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., Vehicle Scrappage and Gasoline Policy, *American Economic Review*, Vol. 105(3): pp. 1312 – 38 (2015), available at: <https://www.aeaweb.org/articles?id=10.1257/aer.20130935> (accessed: May 22, 2026).

2050 and extrapolated at the final (stable) growth rate through CY 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 CY 2050, using a data set that encompasses projections at least through CY 2050 is essential.

NHTSA does not use U.S. unemployment rate and per capita personal disposable income to capture the cyclical component of the macro-economy. Instead, NHTSA uses the GDP growth rate to capture the cyclical component. Since these three variables are highly correlated, the Model only may 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 show evidence of autocorrelation in the error terms that is absent when GDP is used instead.

4.2.2.2.1.4. *Cash for Clunkers*

In 2009, the Car Allowance Rebate System (CARS) was enacted by Congress, with the intent to stimulate the economy through automobile sales and accelerate the retirement of older, less fuel-efficient and less safe vehicles.⁵⁹⁴ 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 1 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 offered in 2009 are presented in Table 4-10 below.

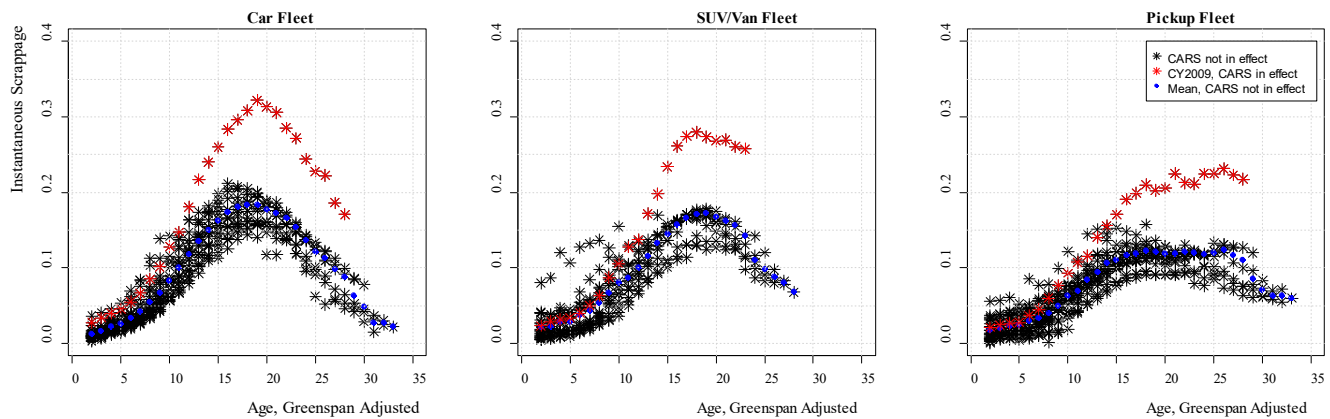
Table 4-10: CARS Fuel-Economy Improvement Required for Rebates by Regulatory Class

	\$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 likely caused some owners to scrap vehicles prematurely in exchange for the trade-in credit. This would explain observed accelerated scrappage rates. The Polk data support this hypothesis as vehicle scrappage rates spiked in 2009. Figure 4-10 shows the observed instantaneous scrappage rate of MYs 1977-2015 by age for CYs 1980-2015. The black stars represent observed scrappage rates for calendar years when the CARS program was not in effect, the red stars represent CY 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.

⁵⁹⁴ Pub. L. No. 111-32, 123 Stat. 1859 (June 24, 2009) <https://www.govinfo.gov/link/plaw/111/public/32>.

Figure 4-10: 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).⁵⁹⁵ They argued that the Canadian market is largely similar to the U.S. market, in part based on the fact that 13 to 14 percent of households purchased new vehicles 1 year pre-recession in both countries. 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 CY 2009. Notable from Table 4-11 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. A dummy variable for CY 2009 interacts with linear and non-linear age variables to represent the effect of the CARS program. The analysis confirms 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

The scrappage model utilizes panel data, which combines repeated observations on multiple individuals or cohorts over time. The data employed by the scrappage model observe 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.⁵⁹⁶ Since the scrappage model uses aggregate model year cohorts to estimate

⁵⁹⁵ Li, S. *et al.*, Evaluating “Cash-for-Clunkers”: Program Effects on Auto Sales and the Environment, *Journal of Environmental Economics and Management*, Vol. 65(2): pp. 175 – 93 (2013), available at: <https://doi.org/10.1016/j.jeem.2012.07.004> (accessed: May 22, 2026).

⁵⁹⁶ Hsiao, C., Analysis of Panel Data, Second Edition, *Cambridge University Press*: New York, NY (1989), available at: <https://assets.cambridge.org/052181/8559/sample/0521818559ws.pdf> (accessed: May 22, 2026) (hereinafter, “Hsiao (1989)”).

scrappage rates by age and time-dependent variables (e.g., new vehicle prices, fuel prices, or GDP growth rate), panel data are necessary to estimate the Model. A major challenge to using panel data is 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.⁵⁹⁷ 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 determines which, if any, of the variables are non-stationary. The agency uses the Augmented Dickey-Fuller test to test the variables.⁵⁹⁸ 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.

Table 4-11: 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 model year/body style cohort	NVPP (IHS/Polk)	I(0)	Levels	N/A
Age	Age defined by the Greenspan and Cohen (1999) adjustment	NVPP (IHS/Polk)	N/A	Levels	Polynomial ⁵⁹⁹
Model year	Model year as defined from dataset	NVPP (IHS/Polk)	N/A	Levels	See model year projections ⁶⁰⁰
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	(-)

⁵⁹⁷ Hsiao (1989).

⁵⁹⁸ Lupi, C., Package ‘CADFtest,’ (2019), available at: <https://cran.r-project.org/web/packages/CADFtest/CADFtest.pdf> (accessed: May 22, 2026).

⁵⁹⁹ 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.

⁶⁰⁰ See the subchapter on modeling durability trends over time. Generally, scrappage rates will decrease with successive model years.

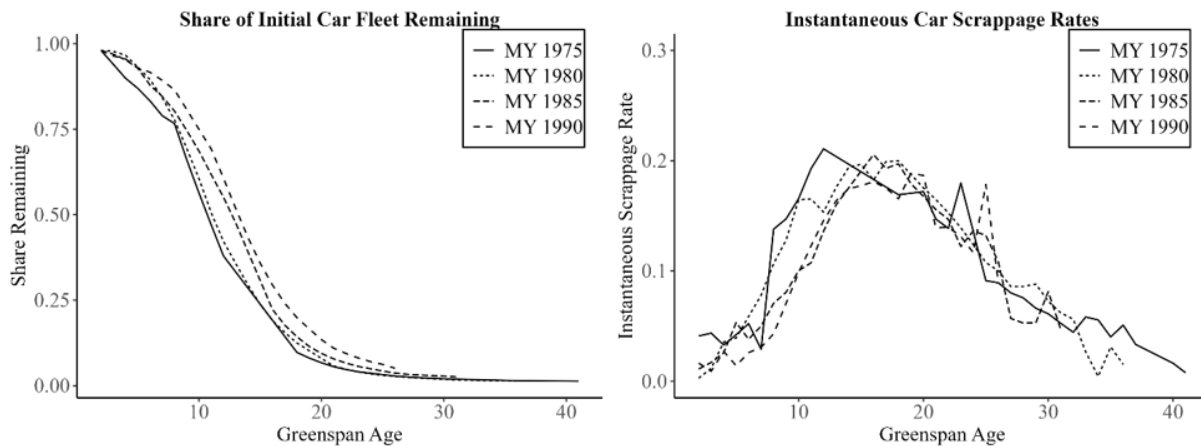
Maintenance/ repair costs	Maintenance/rep air CPI (fixed to 2016)	BLS	I(1)	Difference	(+)
Prices of substitutes	Average new vehicle prices less 30 months fuel savings in current year (\$2018)	NADA, EIA, EPA trends	I(1)	Difference	(-)
Prices of usage	Cost-per-mile of model year/body style cohort in current year (\$2024/100 mile)	EIA, EPA trends	I(1)	Difference	(+)
Prices of usage	Fuel share weighted fuel prices for model year/body style cohort in current year (\$2024)	EIA, EPA trends	I(1)	Difference	(-) ⁶⁰¹

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 model year cohorts 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 4-11 to Figure 4-13 shows the survival and scrappage patterns of different model year cohorts with vehicle age for cars, SUVs/vans and pickups, respectively. Cars have the most pronounced durability pattern. Figure 4-11 shows that newer model year cohorts 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.

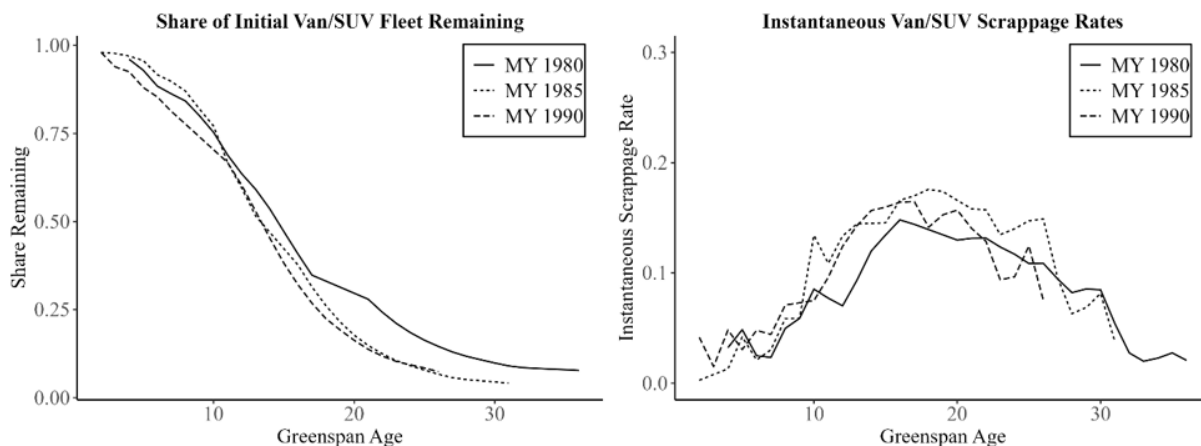
⁶⁰¹ Since the cost-per-mile is included, the change in fuel prices should capture only a capital constraint where increasing fuel prices will result in less capital to scrap a used vehicle and replace it.

Figure 4-11: Survival and Scrappage Patterns of Cars by Greenspan Age



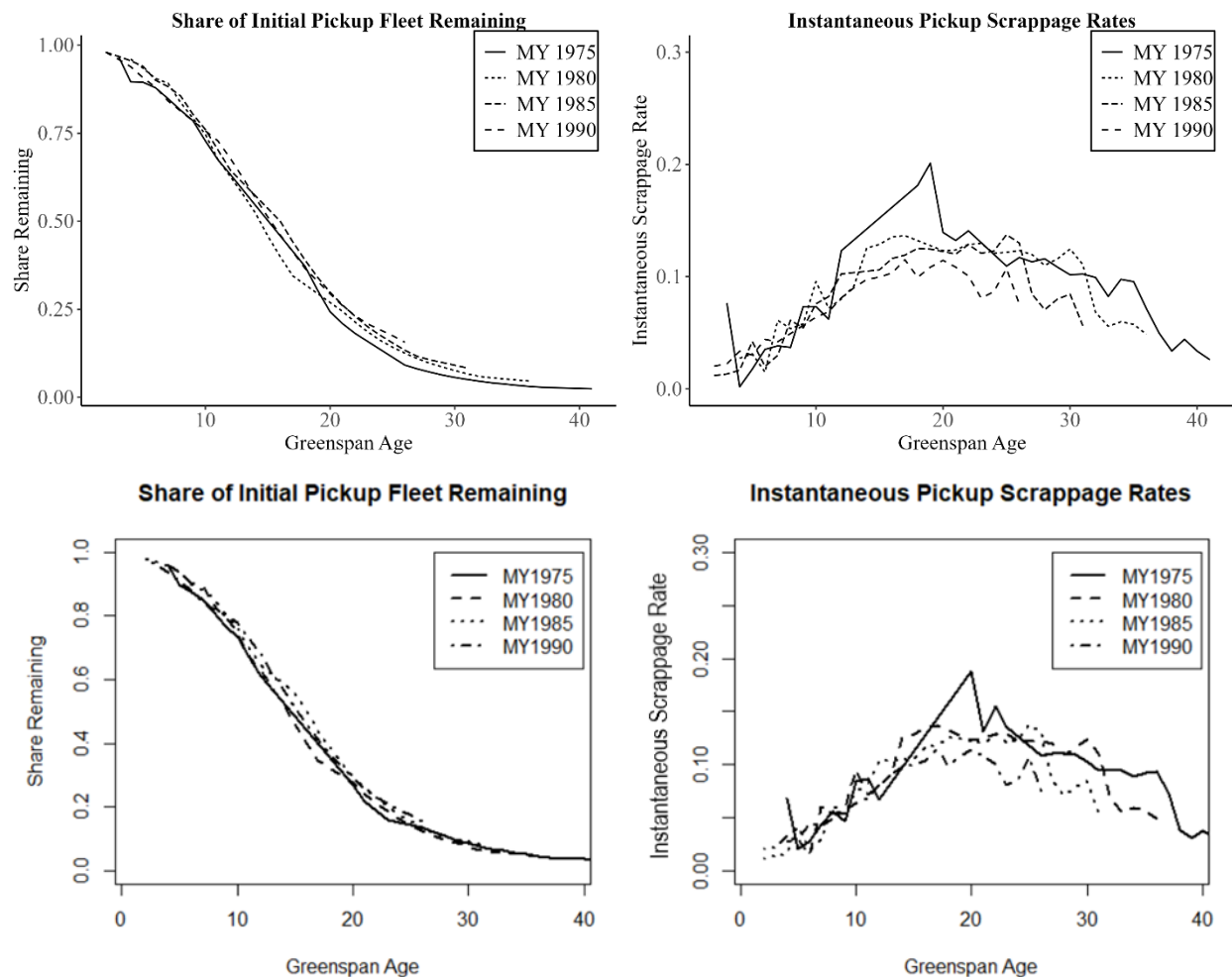
SUVs/vans have a less pronounced durability pattern. MY 1980 live longer than MY 1985 and MY 1990. This is likely due to a switch of many SUVs/vans based on car chassis rather than pickup chassis over time. However, through the later model years, the durability trend is similar to cars. The lack of a continuous trend in durability of SUVs/vans makes the way this trend is captured particularly important.

Figure 4-12: 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 model year cohorts as a continuous variable problematic. Such a parametric form does not allow for each model year to have its own durability pattern.

Figure 4-13: Survival and Scrappage Patterns of Pickups by Greenspan Age



NHTSA models the natural log of model year as a continuous variable interacted with age to capture an increasing trend of vehicle durability for the younger ages that is diminishing. However, enforcing a parametric form on a continuous model year excludes the possibility of including model year specific fixed effects and required durability to have a parametric trend with successive vintages. As seen above, SUVs/vans and pickups do not follow this trend; therefore, this constraint is too restrictive, at least for these body styles.

Instead of regressing the natural log of the model year cohort share in the remaining models, the agency's analysis compares several forms of the share remaining from the previous period as an independent variable, as seen in Table 4-12 through Table 4-14, below. Since the logistic instantaneous scrappage rate is stationary (it is independent of the previous period's 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

$$\ln\left(\frac{S_{MY,CY}}{1-S_{MY,CY}}\right) = \beta_0 * Age_{MY,CY} + \beta_1 * Age^2_{MY,CY} + \beta_2 * Age^3_{MY,CY} + \beta_3 * Share\ Remaining_{MY,CY} +$$

$$\beta_4 * (Age_{MY,CY} * Share\ Remaining_{MY,CY}) + \beta_5 * (Age^2_{MY,CY} * Share\ Remaining_{MY,CY}) +$$

$$\beta_6 * Diff(New\ Price-FS-TaxCredits)_{CY} + \beta_7 * Diff(Fuel\ Price)_{CY} + \beta_8 * Diff(CPM_{MY})_{CY} +$$

$$\beta_9 * GDP\ Growth_{CY} + \beta_{10} * I[CY2009] + \beta_{11} * (I[CY2009] * I[Age \geq 25]) +$$

$$\beta_{12} * I[CY2010] + \beta_{13} * (I[CY2010] * I[Age \geq 25]) + FixedEffects_{MY}$$

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 4-11 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 and pickup 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 36 months of undiscounted fuel savings for all body styles. While tax credits for new vehicles related to the 2022 Inflation Reduction Act (IRA) are not present in the data during the years used to estimate the scrappage model (1975-2017), they are present in the first year projected by the CAFE Model.⁶⁰² 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 is 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 price, 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 4-11, the first difference of all of these variables is used in modelling.

⁶⁰² These include the Clean Vehicle Credit (26 U.S.C. 30D), the Credit for Qualified Commercial Clean Vehicles (26 U.S.C. 45W), and the Advanced Manufacturing Production Credit (26 U.S.C. 45X). See Final TSD Chapter 2.5.1 for more detail about how NHTSA models these credits in its analysis.

GDP Growth represents the (real) GDP growth rate for the period. This captures the cyclical components of the macro-economy. Chapter 4.2.2.2.1.3, 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 CY 2009 and CY 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 years and older. Since only vehicles under 25 were eligible for the program, this flexibility is important to control for the program correctly.

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

$$S = \frac{e^{\sum \beta_i X_i}}{1 + e^{\sum \beta_i X_i}}$$

In the equation above, $\sum \beta_i X_i$ represents the right-hand side of the above model specification.

Table 4-12: Car Specifications with Alternative Durability Constructions

Variable	Share Remaining, Quadratic	Preferred: Share Remaining, Linear	Share Remaining, Constant
Age	0.1257355*** (0.0070828)	0.1702192*** (0.006964)	0.440508*** (0.0025385)
Age2	-0.005117*** (0.0003699)	-0.0085325*** (0.0003345)	-0.0213387*** (0.0001635)
Age3	0.000002 (0.0000063)	0.0000605*** (0.0000054)	0.0002494*** (0.0000037)
Share Remaining	-2.8430103*** (0.0460117)	-2.8900354*** (0.045858)	-1.5421736*** (0.0288211)
Age *Share Remaining	0.2688544*** (0.0061349)	0.1432191*** (0.0035927)	
Age2 *Share Remaining	-0.0105577*** (0.0005507)		
Diff(New Price - Fuel Savings)	-0.0000807*** (0.000001)	-0.0000676*** (0.0000013)	-0.0000762*** (0.0000016)
Diff(Real Gas Price)	-0.3634687*** (0.016738)	-0.5719423*** (0.0139369)	-0.5495174*** (0.0226407)
Diff(Used Cost Per 100 miles)	0.0315758*** (0.0032573)	0.0850085*** (0.0025823)	0.0601523*** (0.0047592)

GDP Growth Rate	0.050997*** (0.0007219)	0.0476706*** (0.0010757)	0.0557159*** (0.0010588)
CY2009	0.0639714** (0.0194567)	0.0727403*** (0.0147424)	0.0738266*** (0.0123536)
CY2009, Ages 25+	0.5010809*** (0.0279331)	0.7655857*** (0.024023)	0.4429346*** (0.0277501)
CY2010	0.282979*** (0.0149821)	0.2880668*** (0.0121901)	0.404581*** (0.0169994)
CY2010, Ages 25+	0.300085*** (0.0249687)	0.2888421*** (0.0164745)	0.158641*** (0.0229134)
Adj-R2	0.898029	0.897568	0.896274
AIC	219	220	228
Woodridge AC P-Value ⁶⁰³	0.002653	0.003208	0.002299

*** p < 0.001, ** p < 0.01, * p < 0.05, p < 0.1

Table 4-13: SUVs/Vans Specifications with Alternative Durability Constructions

Variable	Share Remaining, Quadratic	Preferred: Share Remaining, Linear	Share Remaining, Constant
Age	0.0578384*** (0.00922)	0.0441125*** (0.0086471)	0.3614882*** (0.0016346)
Age2	-0.0028535*** (0.000204)	-0.0025576*** (0.000188)	-0.0084353*** (0.0000372)
Share Remaining	-2.9507597*** (0.0931985)	-3.1703155*** (0.0853661)	0.6612724*** (0.0307032)
Age *Share Remaining	0.1429558*** (0.0098413)	0.1960092*** (0.0045385)	
Age2 *Share Remaining	0.0038922*** (0.0007247)		
Diff(New Price - Fuel Savings)	-0.0000036*** (0.0000011)	-0.0000089*** (0.0000007)	0.0000121*** (0.0000015)
Diff(Real Gas Price)	-0.4143496*** (0.0343114)	-0.0990203*** (0.025202)	0.1531584*** (0.0221603)
Diff(Used Cost per 100 Miles)	0.0678471*** (0.0054664)	0.020296*** (0.0037798)	-0.0221708*** (0.0035131)
GDP Growth Rate	0.0670157*** (0.00096)	0.0697549*** (0.0007858)	0.0702781*** (0.0008004)

⁶⁰³ 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.

CY2009	0.4075355*** (0.0204956)	0.3909382*** (0.0181106)	0.4280408*** (0.0203873)
CY2009, Ages 25+	0.2235058*** (0.0495789)	0.3106498*** (0.0413997)	0.545402*** (0.0418842)
CY2010	0.2086204*** (0.0192787)	0.1261091*** (0.0166216)	0.0452617** (0.0164732)
CY2010, Ages 25+	-0.0116971 (0.0650037)	0.1480228*** (0.0256204)	0.3227516*** (0.0283573)
R2	0.9102964	0.912256	0.893704
AIC	106	91	208
Woodridge AC P- Value ⁶⁰⁴	0.0005074	0.018522	0.000000

*** p < 0.001, ** p < 0.01, * p < 0.05, p < 0.1

Table 4-14: Pickup Specifications with Alternative Durability Constructions

Variable	Share Remaining, Quadratic	Preferred: Share Remaining, Linear	Share Remaining, Constant
Age	0.0546807*** (0.0050206)	0.0444685*** (0.0048149)	0.2713347*** (0.0014716)
Age2	-0.0021221*** (0.000101)	-0.0016723*** (0.000091)	-0.0057276*** (0.0000244)
Share Remaining	-2.0576577*** (0.0552494)	-2.0014995*** (0.0555194)	0.7210447*** (0.0281117)
Age *Share Remaining	0.0550886*** (0.0054535)	0.1438551*** (0.0030846)	
Age2 *Share Remaining	0.0055107*** (0.0002819)		
Diff(New Price - Fuel Savings)	-0.0000614*** (0.000001)	-0.0000541*** (0.0000008)	-0.0000348*** (0.0000014)
Diff(Real Gas Price)	-0.0968882*** (0.0200699)	-0.3244839*** (0.0133438)	-0.2368444*** (0.030286)
Diff(Used Cost per 100 Miles)	0.0137646*** (0.0031214)	0.0548433*** (0.0022026)	0.0448256*** (0.0050334)
GDP Growth Rate	0.0634998*** (0.0010256)	0.0587337*** (0.000791)	0.0522179*** (0.001021)
CY2009	0.5510889*** (0.0148841)	0.335058*** (0.009507)	0.5246689*** (0.0215271)

⁶⁰⁴ 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.

CY2009, Ages 25+	0.0977145*** (0.0267172)	0.3113689*** (0.029511)	0.1391113*** (0.0358737)
CY2010	0.0856259*** (0.0088583)	0.1243409*** (0.0070926)	0.1756698*** (0.0135063)
CY2010, Ages 25+	0.4125322*** (0.0087513)	0.3968208*** (0.0073726)	0.2376862*** (0.0191086)
R2	0.922537	0.922075	0.917896
AIC	-67	-65	-34
Woodridge AC P- Value ⁶⁰⁵	0.505835	0.428528	0.027743

*** p < 0.001, ** p < 0.01, * p < 0.05, p < 0.1

As Table 4-12 shows, the linear form of the interaction of age and share remaining does not show evidence of autocorrelation and has nearly equal measures of goodness of fit (low Akaike Information Criterion (AIC)—an estimator of prediction error and measure of model quality, and high R2) as the quadratic fit.⁶⁰⁶ Since these measures are similar for the two specifications, and since the linear model produces statistically significant point estimates for all terms, it was chosen as 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 has 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 switches 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 20, 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 19, after which a higher share remaining predicts a higher instantaneous scrappage rate.

As Table 4-13 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 to that of cars. Taking the ratio again of the share remaining to the share remaining interacted with age, for ages 0 to 17 a higher share remaining predicts lower instantaneous scrappage, and for ages beyond 17 it predicts a higher instantaneous scrappage rate.

Table 4-14 shows both the quadratic and linear specifications of the durability effect for pickups and shows autocorrelation in the error structures. For this reason, despite having a slightly lower measure of goodness of fit, the constant share remaining model is the preferred specification. For this model, share

⁶⁰⁵ Note: Wooldridge Test For AR(1) Errors In FE Panel Models implemented as ‘pwtartest’ 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.

⁶⁰⁶ Note that the parameters of these scrappage models are estimated on data where the stock of used vehicles is predominantly ICE vehicles. It is not clear whether scrappage decisions will substantively change in future years when zero emissions vehicles (ZEVs), SHEVs, and PHEVs constitute a larger share of new vehicle shipments, as consumer demand characteristics 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.

remaining has a constant, positive coefficient, meaning that at all ages a higher share remaining will imply a higher scrappage rate.

4.2.2.3.3.1. *Projecting Durability in the CAFE Model*

The left graphs in Figure 4-14 through Figure 4-16 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 more complicated than merely fitting to all fixed effects.

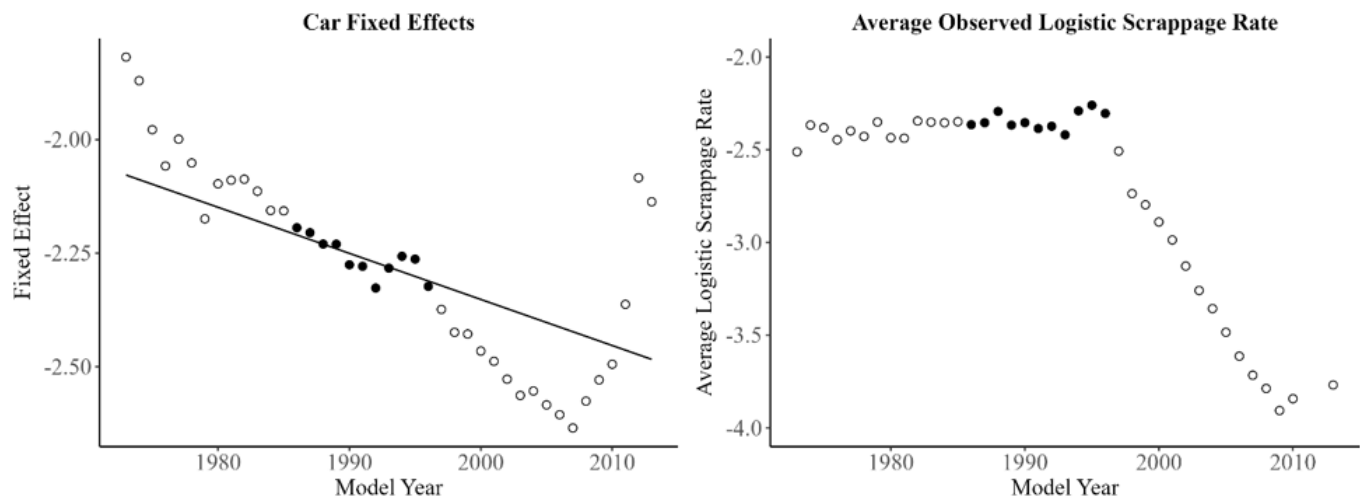
NHTSA determines which part of this trend is likely due to increases in vehicle durability (and should be projected forward) and which part of the trend may conflate other factors.

The right graphs in Figure 4-14 through Figure 4-16 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 MY 1996 and beyond 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. MY 1996 is the first model year that will be at least age 20 at the most recent year of data used to estimate the scrappage models (CY 2016). This means that all MY 1996 and beyond have not yet reached the age where the instantaneous scrappage rate will be the highest for the cohort. The fixed effects could be biased downward (consistent with the sharper downward slope in the fixed effects for most body styles for MY 1996 and beyond) 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 MY 1996 is more stable is because each data point in the average has increasingly less effect on the average as more data enters the Model. For MY 1996 and older there are at least 18 data points (NHTSA starts the scrappage at age 2, by which point all of a model year effectively has been sold), and each has 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 MY 1996. As a result, NHTSA does not consider the trend in fixed effects after MY 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.

When considering which model year fixed effects should be included, an important factor is whether there are discrete shifts in the types of vehicles in the market. For cars, an increasing market share of vehicles produced by Japanese automakers, 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 4-14, which follow a steeper trend before MY 1980.

Figure 4-14: 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.⁶⁰⁷ As Figure 4-15 shows, the fixed effects before 1986 show inconsistent trends; these are likely due to changes in what was considered a van/SUV over time. NHTSA builds the trend of fixed effects from MYs 1986-1996 for these reasons.

⁶⁰⁷ Hunting, B., 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: May 22, 2026).

Figure 4-15: Trends in Fixed Effects for Preferred Van/SUV Specification

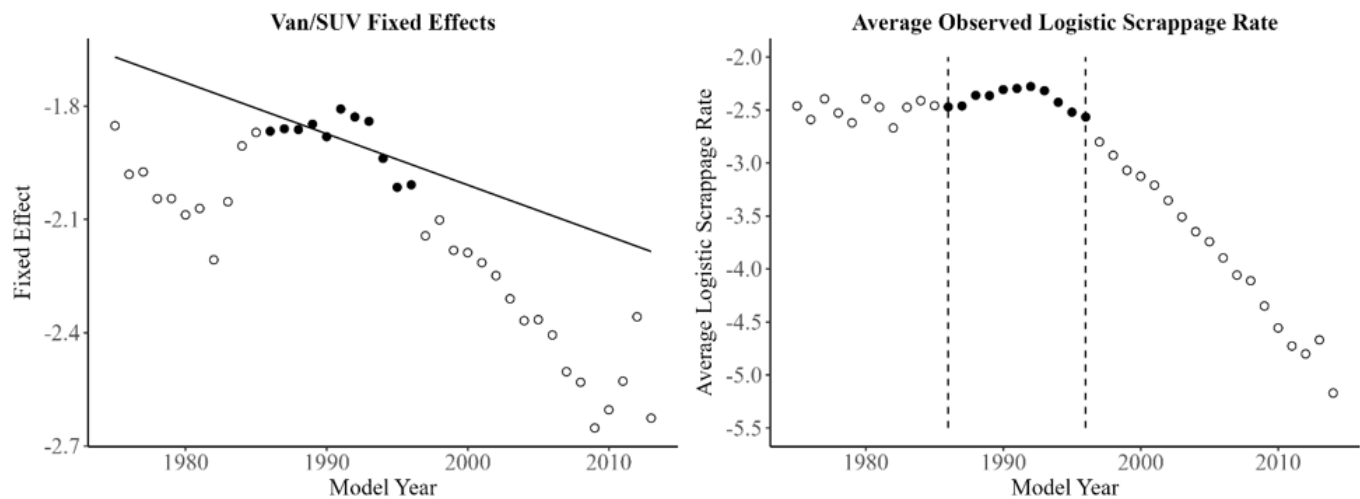
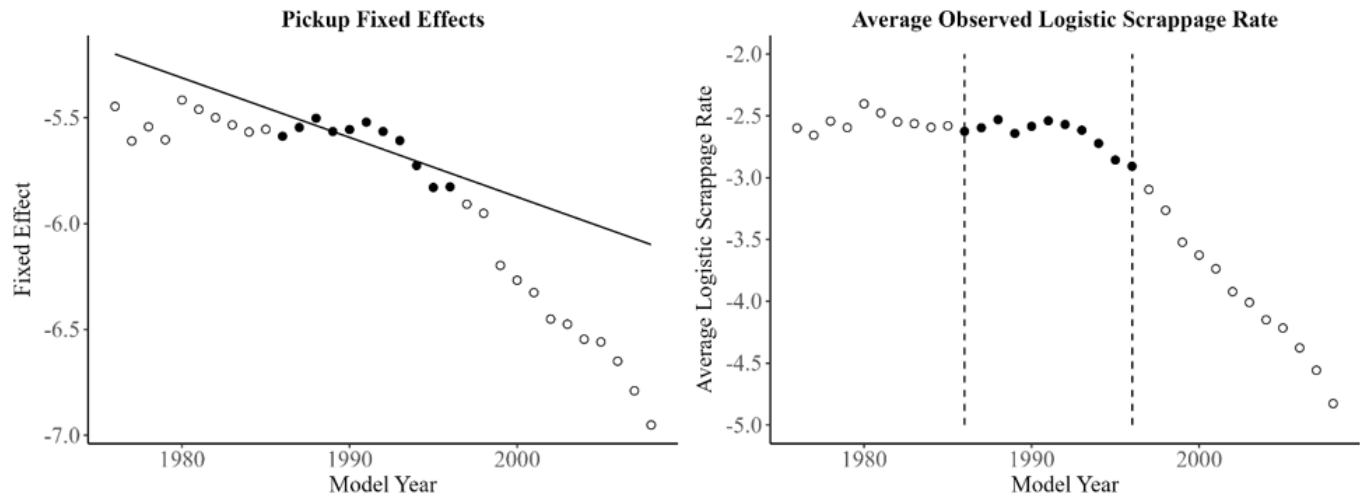


Figure 4-16: Trends in Fixed Effects for Preferred Pickup Specification



While the trend for pickups and cars could be extrapolated before 1986, NHTSA opts to keep the fixed effects included constant for all body styles. Thus, the projections are built from MYs 1986-1996 fixed effects. Table 4-15 below displays the linear regressions shown as the line on the left side of Figure 4-14 through Figure 4-16. The durability cap represents the last model year where the durability trend is assumed to persist. The agency caps the durability impacts at MY 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 MY 2005 are assumed to have the same initial durability as MY 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 4-15: Durability Inputs in the CAFE Model

Coefficients	Inputs	Cars	Vans/SUVs	Pickups
β_{12}	Intercept	17.930	25.075	50.369
β_{13}	Model Year	-0.010	-0.014	-0.028

β_{14}	Model Year Durability Cap	2005	2005	2005
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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 Equation⁶⁰⁸

$$\ln\left(\frac{S_{MY,CY}}{1-S_{MY,CY}}\right) = \beta_0 * Age_{MY,CY} + \beta_1 * Age_{MY,CY}^2 + \beta_2 * Age_{MY,CY}^3 +$$

$$Share\ Remaining_{MY,CY} * (\beta_3 + \beta_4 * Age_{MY,CY}) +$$

$$Diff(New\ Price-FS-TaxCredits)_{CY} * (\beta_5 + \beta_6 * Age_{MY,CY} + \beta_7 * Age_{MY,CY}^2 + \beta_8 * Age_{MY,CY}^3) +$$

$$\beta_9 * Diff(Fuel\ Price)_{CY} + \beta_{10} * Diff(CP100M_{MY})_{CY} +$$

$$\beta_{11} * GDP\ Growth_{CY} + \beta_{12} + \beta_{13} * MY_{MY} - ifelse(MY_{MY} > \beta_{14}, \beta_{13} * (MY_{MY} - \beta_{14}), 0)$$

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 MY 2005 and enters as 2005 for all vehicles MY 2005 and beyond.

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 is predicted. The instantaneous scrappage is 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 CO₂ emissions, and associated costs and benefits. The CAFE Model Documentation details how the scrappage model is projected within the simulations.

4.2.2.3.3.2. Decay Function for Oldest Ages

Nearly 6 percent of the MY 2015 van/SUV fleet and 8 percent of the pickup fleet is projected to persist until age 40. This is unrealistic and likely since the agency does not observe enough model years for those ages and thus 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 4-16 below, shows the inputs used for this analysis.

⁶⁰⁸ While tax credits related to the 2022 IRA 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. 50 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.

Table 4-16: 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 the decay function to begin operating at age 30 as the observed historical trends run through age 30.

The decay function is implemented in the Model using the following conditions for the coefficients in Table 4-16:

$$\text{If } (age < \beta_{15}), S = \frac{e^{\sum \beta_i X_i}}{1 + e^{\sum \beta_i X_i}}$$

$$\text{And: } Population_{MY, CY+1} = Population_{MY, CY} * (1 - S_{MY, CY}).$$

$$\text{If } (age \geq \beta_{15}),$$

$$Population_{MY, CY+1} = Population_{MY, CY=\beta_{15}} * \exp^{rate * t}$$

$$\text{Where: } t = (age + 1 - \beta_{15})$$

$$\text{And: } rate = \frac{\ln\left(\frac{\beta_{16}}{Population_{MY, CY=\beta_{15}}}\right)}{40 - \beta_{15}}$$

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. 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 it highlights the practical constraints of modeling complex decisions like vehicle scrappage in both an econometric and (subsequent) simulation context.

As noted earlier, households retire used vehicles when their market value drops below the cost of maintenance necessary to keep them in service. Therefore, 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 only can be included as a calendar year effect. Using the measure in that role results in a poorer fit; therefore, the

agency excludes 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 have changed over time, meaning that the absolute amount of recoverable scrap steel is not constant. To estimate the value to scrap a vehicle appropriately, 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 attempts to use a coarse approximation of scrappage value by using the BLS scrap steel CPI; but similar to maintenance, inclusion of 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 considers a more granular approach of estimating the impact of discrete vehicle traits, such as HP 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 considers using terms that would more directly capture the value of improved fuel economy in newer vehicles, such as the CPM of new vintages, rather than subtracting the first 36 months of undiscounted fuel prices from the price of new vehicles.⁶⁰⁹ These variables do 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 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 considers 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 act as a barrier to entry, but 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 influenced heavily by interest rates. The agency tests 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 most of the effect of auto loan

⁵⁵ While tax credits related to the 2022 IRA 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. 50 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.

rates should be captured by using the interest rate facing the Federal Government. For vans/SUVs, the Model with interest rates have a poorer fit and shows evidence of autocorrelation in the error structures. For pickups, including interest rates change the sign on CPM. This change was irregular as 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 VMT by gas-powered vehicles—determine many of the effects of CAFE standards. The agency’s CAFE Model employs different methodologies to estimate VMT for each calendar year included in the analysis period (here, CYs 2024-2050), and the resulting estimates 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 of gas-powered vehicles remaining in use during that year and summing the results. This measure excludes VMT drivers voluntarily choose to undertake because fuel economy standards have reduced the fuel cost of driving, which explains why it is referred to as non-rebound VMT.
- The “VMT Constraint” is used to adjust total non-rebound VMT in each calendar year to be identical among the baseline and all regulatory alternatives. The VMT Constraint is set at the total of the No-Action Alternative’s non-rebound, gas-powered VMT. The agency assumes that household travel demand is relatively inelastic and will not be directly affected by the stringency of CAFE standards.
- “Reallocated VMT” is the difference in total VMT between the VMT Constraint and unadjusted non-rebound VMT during any future calendar year, for each regulatory alternative. It is the amount by which total unadjusted non-rebound VMT must be increased or reduced during the calendar year so that adjusted non-rebound VMT equals the VMT Constraint for that calendar year. 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.
- Rebound VMT is the amount of additional driving done in response to changes in the cost of driving due to improvements in fuel economy since 2016. NHTSA assumes that, beyond the level of the VMT constraint, demand for travel is somewhat responsive to the cost of driving, or elastic. Differences in rebound VMT between alternatives determine their difference in total VMT, since non-rebound VMT is held equal to the constraint.

The CAFE Model calculates total annual VMT by taking the product of average annual use of each vehicle cohort (defined by vehicle type, model year when originally produced, and current age) in the on-road fleet and the number of vehicles from that model year cohort remaining in use. The number of used vehicles remaining in use is itself a function of historical new vehicle sales and vehicles’ retirement rates over their lifetimes.⁶¹⁰ In conjunction with the composition of the “inherited” gas-powered vehicle fleet by type (e.g., cars, SUVs/vans, or 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

⁶¹⁰ While there is heterogeneity in terms of average VMT within a vehicle type/model year cohort, NHTSA does not account for this heterogeneity in its non-rebound VMT allocation. This may over or understate some of the effects estimated by the CAFE Model if vehicle usage is highly correlated with other attributes that also determine the size of the effects.

scrappage of older vehicles—jointly determine projected total VMT for future years under each regulatory alternative considered.

Decisions about alternative stringencies for CAFE standards examine their incremental costs and benefits across alternatives. It is 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 initially constrains its forecast of VMT under each regulatory alternative to be equal.

NHTSA first uses a baseline simulation from the CAFE Model under No-Action assumptions and uses the gas-powered fleet to generate a forecast of the number of gas-powered vehicles in each age-body style cohort remaining on the road in each future calendar year. Using this profile of the fleet and the mileage accumulation schedule, NHTSA develops a “bottom up” forecast of aggregate VMT in each calendar year by multiplying the number of vehicles on the road in each age-body style cohort by the annual number of miles a vehicle of that body style is expected to be driven when it reaches that age.

This approach generates a reasonable forecast for aggregate VMT for the standard-setting fleet, which considers gas-powered new vehicles in future model years. Described in more detail below, the 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 constraint produces the desired effect of making any differences in aggregate VMT among regulatory alternatives during future calendar years solely 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 LD VMT and each alternative’s internally generated “bottom-up” forecast to represent the composition of total VMT. 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 vehicle model year cohorts comprising that year’s fleet.

NHTSA attempted to incorporate estimates of changes to the new and used vehicle markets at the most practical levels of aggregation and worked to ensure that these effects produce fleetwide VMT estimates that are consistent with current projections reflecting NHTSA’s economic assumptions. While NHTSA continues to explore approaches to improve the realism of CAFE policy simulations, 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

NHTSA estimates the portion of costs and benefits occurring each calendar year that are attributed to the ownership and use of vehicles from each model year cohort. NHTSA does this to account for societal costs and benefits associated with vehicle use under various CAFE alternatives. 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. NHTSA refers to these as “mileage accumulation schedules.” As described in greater detail in the following sections, these mileage accumulation schedules represent an initial estimate of average annual vehicle use at each age during some base year and are adjusted subsequently in each future calendar year based on forecasted fuel prices and the aggregate travel demand determined by a separate forecasting model. For the analysis, NHTSA relies 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 irregular 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 tracks 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 the analysis of 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, Polk, accumulates odometer readings for individual vehicles from State inspection programs, title changes, and maintenance events, among other sources. The 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.

NHTSA computes the rate of driving (miles per year, or month) between observations for each vehicle by using the observation date and accumulated miles (represented by the odometer reading). This method provides reliable estimates of variation in vehicle use with increasing age rather than computing a simple ratio of total miles traveled to age. This is an improvement over schedules built from cross-sectional data, which assumes the VMT-to-age ratio remains fixed across all vehicle ages.⁶¹¹ In particular, calculating the rates of mileage accumulation using successive observations of the same vehicle resolves the attrition bias (where some vehicles disappear from a cross-sectional data sample because of the intensity with which they are used) and matches the approach to estimating driving rates with panel data in other studies.⁶¹²

4.3.2.2. Methodology for Constructing the Schedules

The data used to construct the schedules initially ranges from between 2 and 50 odometer readings per vehicle from over 251 million unique vehicles. While most readings have plausible reading dates, odometer counts, and implied usage rates, some of the readings appear unrealistic and receive additional scrutiny. NHTSA develops and applies criteria to identify and remove readings that are 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, are removed from the analysis. Such “cleaning” of datasets is typically necessary, and each step in the process is recorded and documented. Table 4-17 shows the number of VINs, reading pairs, and average readings per VIN by body style for the cleaned dataset.⁶¹³

Table 4-17: Summary of Polk Total Vehicle Miles Traveled 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

⁶¹¹ Lu, S., Vehicle Survivability and Travel Mileage Schedules, DOT HS 809 952, Washington, D.C., NHTSA (2006), available at: <https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/809952> (accessed: May 22, 2026).

⁶¹² The use of the 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 available from other data sources. These advantages are discussed in detail in prior rulemakings. For reference, see 84 FR 24678 (Apr. 30, 2020).

⁶¹³ Data in this table for cars, SUVs, and pickups are identical to values used in the 2022 final rule.

SUVs/vans	66,857,117	212,656,710	4.2
Pickups	29,926,984	83,208,986	3.8

NHTSA created a random sample of one million reading pairs from the refined dataset, where each pair represents an initial odometer/date reading and a subsequent odometer/date reading from the same vehicle. This is because analyzing the entire dataset is computationally demanding and unnecessary to provide the desired level of statistical precision. Two conditions are applied to the sampling. The first controlled for Polk’s censoring in the odometer readings recorded in the dataset (described below), while the second ensures 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 of time between odometer readings are correlated with higher usage rates, so further filtering of the data sample is incorporated in the regression analysis. Once these filters are applied, NHTSA considers several polynomial fits to the average odometer readings by age and body style and used NHTSA’s preferred models to construct the mileage accumulation schedules used in this analysis.

The dataset constructed by Polk includes an upper limit on reported odometer readings of 250,000 miles. For this reason, NHTSA excludes readings recorded exactly as 250,000 miles. The censoring could bias estimates of usage rates if odometer readings and future usage rates are correlated. Vehicles with reported odometer readings of exactly 250,000 miles in the dataset almost certainly have higher true odometer readings. While this represents a limitation of the dataset, the benefits of observing actual usage through 30 years of a vehicle’s life more than compensate for the limitation.

The Polk dataset represents the usage of vehicles remaining in use at the time of the sample (the end of the first quarter of 2017) and the observations are thus conditional on survival. 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-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, NHTSA applied a second filter when sampling the data set: NHTSA 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 toward lower levels. Figure 4-17 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 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 decrease gradually with increasing age.

Figure 4-17: Distribution of SUV Usage Rates by Age

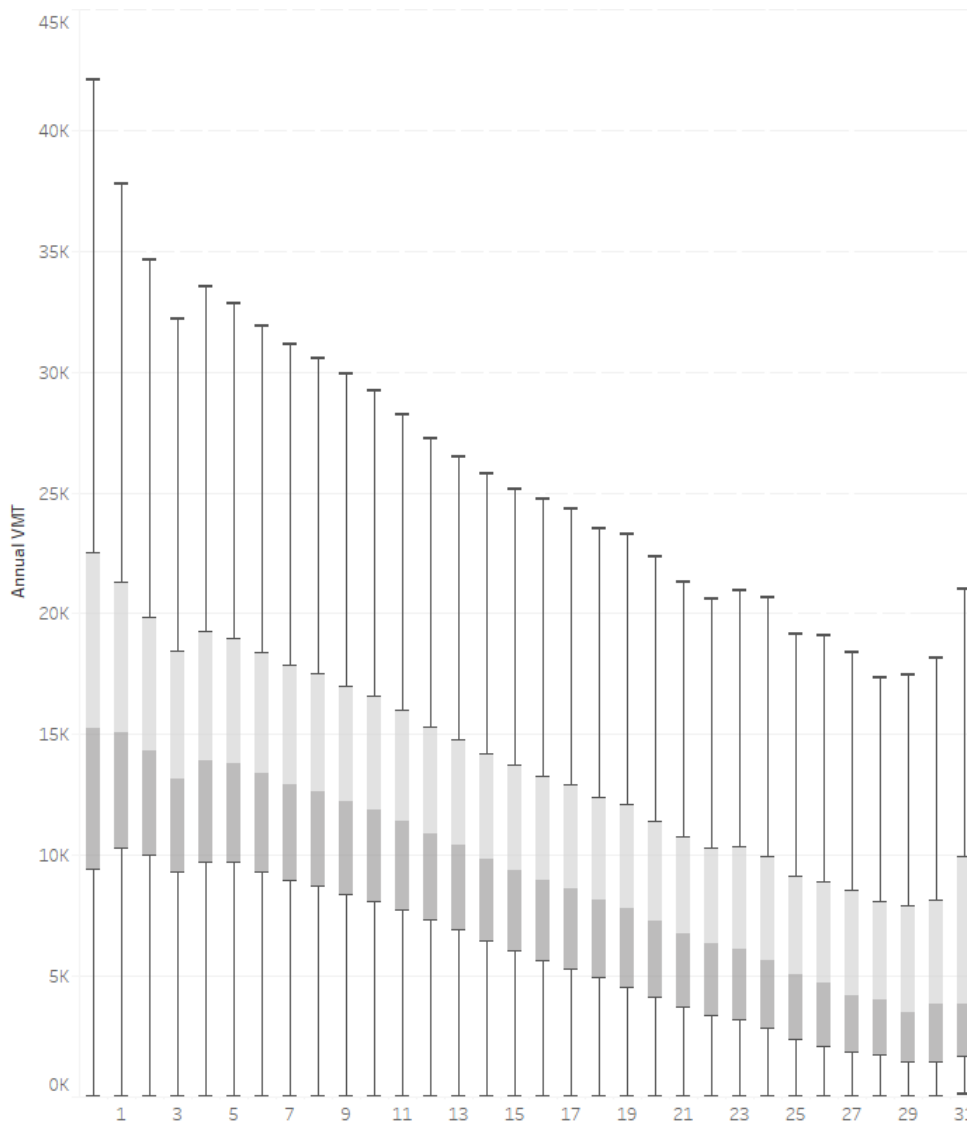
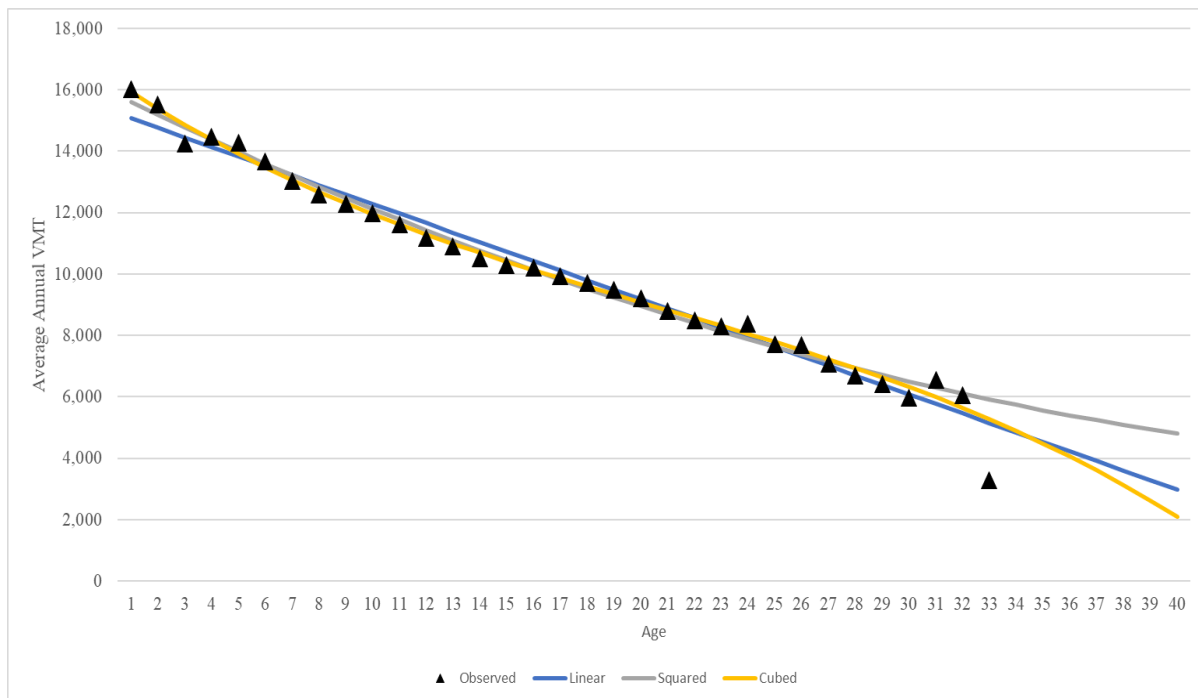


Figure 4-17 also shows that average annual VMT occasionally fluctuates at certain ages, which is likely attributable to changes in ownership. For example, average annual use declines slightly at age three and then increases at age four before resuming its gradual decline, which is probably a consequence 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 who plan to use them more.

The agency tests several relationships to summarize the pattern of vehicle use with age. Because the CAFE Model carries no disaggregated representation of vehicle ownership or usage, using the average mileage 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 LD VMT. Figure 4-18 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.⁶¹⁴ 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 and pickups. SUVs were best fit by a quadratic polynomial. The resulting annual VMT schedules based on these functions are shown in Table 4-18.

Figure 4-18: Polynomial Fits for Average Car Total Vehicle Miles Traveled



4.3.2.3. Mileage Accumulation Schedules for the Base Year 2016

As Table 4-18 illustrates, passenger cars are driven slightly less than either SUVs or pickup trucks on average.⁶¹⁵ Importantly, these annual driving rates represent the estimated annual mileage accumulation of a vehicle, of a given body style, which 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 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. An artifact of using the average usage is that vehicle owners who drive more than the average will benefit more than NHTSA’s modeled estimates from improved fuel economy, while drivers who use their vehicles less intensively will benefit less.

⁶¹⁴ 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.

⁶¹⁵ These same mileage accumulation schedules can also be found in the CAFE Model Input File “parameters,” on the “Vehicle Age Data” tab.

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 true that 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 4-18: Total Vehicle Miles Traveled Schedule by Body Style and Age

Vehicle Age	Cars	Vans/ SUVs	Pickups
0	15,922	16,234	18,964
1	15,379	15,805	17,986
2	14,864	15,383	17,076
3	14,378	14,966	16,231
4	13,917	14,557	15,449
5	13,481	14,153	14,726
6	13,068	13,756	14,060
7	12,677	13,366	13,448
8	12,305	12,982	12,886
9	11,952	12,605	12,372
10	11,615	12,234	11,903
11	11,294	11,870	11,476
12	10,986	11,512	11,088
13	10,690	11,161	10,737
14	10,405	10,816	10,418
15	10,129	10,477	10,131
16	9,860	10,146	9,871
17	9,597	9,820	9,635
18	9,338	9,501	9,421
19	9,081	9,189	9,226
20	8,826	8,883	9,047
21	8,570	8,583	8,882
22	8,313	8,290	8,726
23	8,051	8,004	8,577
24	7,785	7,724	8,433
25	7,511	7,450	8,290
26	7,229	7,183	8,146
27	6,938	6,923	7,998

28	6,635	6,669	7,842
29	6,319	6,421	7,676
30	5,988	6,180	7,497
31	5,641	5,946	7,302
32	5,277	5,718	7,089
33	4,893	5,496	6,853
34	4,488	5,281	6,593
35	4,061	5,072	6,305
36	3,610	4,870	5,987
37	3,133	4,674	5,635
38	2,629	4,485	5,248
39	2,096	4,303	4,821

4.3.3. Using the Mileage Accumulation Schedules to Estimate Total Vehicle Miles Traveled

The prior subchapter describes the process for deriving mileage accumulation schedules using observed data through CY 2016. NHTSA uses the VMT accumulation schedule for two separate calculations. First, it is used to produce a forecast of aggregate non-rebound VMT, which is used as the VMT Constraint for the gas-powered fleet. Second, the VMT accumulation schedule is used to “re-allocate” VMT across vehicles in each alternative. This is necessary to account for the effects of alternative CAFE standards on the number of vehicles, the share of vehicles of different ages, and the share of vehicles in each body style group. This reallocation process divides up the constrained non-rebound VMT across body-style-age cohorts.

4.3.3.1. Constraining Reference Total Vehicle Miles Traveled

The CAFE Model constrains each year’s “non-rebound” VMT in the regulatory alternatives to match its annual value under the No-Action Alternative. To produce this value, the estimates of driving at each age comprising the mileage accumulation schedules are multiplied by the projected number of vehicles of that age in the current year’s fleet under the No-Action Alternative, as determined after considering the sales and scrappage effects. The sales, fleet share, and scrappage model are each explained in the Final TSD Chapter 4.2.

Constrained non-rebound VMT for a given calendar year is calculated using the following equation where $Population_{A,S}$ equals the number of vehicles in body style S and age A remaining on the road in calendar year CY , and $VMT_{A,S}$ represents the corresponding average usage per vehicle for the cohort as given in the VMT accumulation schedule.

Equation 4-10: Reference Non-Rebound Total Vehicle Miles Traveled

$$MI_{CY}^{NonRebound} = \sum_S \sum_A^{Styles\ Ages} Population_{A,S} VMT_{A,S}$$

This methodology does not account for changes in non-rebound VMT in response to macroeconomic factors, beyond their effects on sales and scrappage. Since the mileage accumulation schedule is fixed across calendar years, each new vehicle will add an equal amount of VMT.

4.3.3.2. Reallocating Total Vehicle Miles Traveled

The process described in the previous subchapter of building up a forecast of total VMT using the mileage accumulation schedules produces a single value for each calendar year. However, since the regulatory alternatives generate effects on sales of new vehicles, scrappage of used vehicles, and changes in the relative cost of driving vehicles within the fleet, it is unlikely that the total VMT for each body style-age cohort will be equal in each year across those alternatives, even if total non-rebound VMT remains fixed.

To reflect these differences, the CAFE Model adjusts the schedules of average annual vehicle use from the odometer data's base year (2016) to future years to account for future changes in fuel prices and the future evolution of fuel economy for vehicles of different ages. It then takes the product of expected VMT from these adjusted schedules with the number of vehicles of each age projected to remain in the fleet to estimate total VMT for each future calendar year. The shares of VMT for each body style-age cohort implied by this exercise can then be applied to the VMT Constraint for each calendar year to determine VMT usage by each cohort. This generates variation in the composition of non-rebound VMT across alternatives, even as the total level of non-rebound VMT remains constant.

The CAFE Model estimates shares of non-rebound VMT by adjusting the 2016 base year mileage accumulation schedules using a measure of future changes in per-mile driving costs. It includes the effects of changes in fuel prices since the base year of 2016, but it omits the effects of fuel economy changes after 2016 from the changes in fuel CPM it calculates for future years. Equation 4-11 shows this measure of the change in fuel CPM for cars and light trucks of different ages during the calendar year.

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} refers to fuel price per gallon during 2016, and FP_{CY} to fuel price per gallon during a future calendar year. FE_{REF} refers to the average FE of the model year cohort that was of age = 2016 – MY during CY 2016. In Equation 4-11, $FE_{MIN(2016, MY)}$ refers to the average fuel economy of cars or light trucks produced during MY 2016 and beyond. As its subscript $MIN(2016, MY)$ indicates, it is the *lower* of the actual fuel economy of cars or light trucks that have reached age = CY – MY during the calendar year and the fuel economy of those that were of that same age during 2016. Equation 4-11 applies to vehicles of all ages during each future calendar year, because the difference between the calendar year and a vehicle's model year determines its age.

In Equation 4-11, the fuel economy in the denominator of the first term is the *minimum* of the actual fuel economy of cars and trucks in that model year and the fuel economy cars or light trucks achieved during MY 2016. In effect, Equation 4-11 assumes that no improvements in fuel economy would have occurred after MY 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 MY 2016. This assumption implies that fuel-economy improvements through MY 2016 *will* be accounted for when calculating shares of non-rebound VMT for any later calendar year, but that further increases in fuel economy after MY 2016 *will*

not be. Thus, increases in average annual VMT per vehicle during CY 2016 and beyond reflect only subsequent changes in (inflation-adjusted) fuel prices.

Combining the adjustments to average annual VMT during the reference year of 2016 for different LDV 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 in each alternative, as shown by Equation 4-12:

Equation 4-12: Unadjusted Total Non-Rebound Total Vehicle Miles Traveled in a Future Calendar Year

$$NonReboundVMT_{CY} = \sum_A^{Ages} \sum_S^{Styles} VMT_{A,S} \cdot (1 + \% \Delta NonRbdCPM_{MY,CY} \cdot \epsilon) \cdot Population_{CY,A,S}$$

where $VMT_{A,S}$ represents average annual mileage for LDVs 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 calendar year CY and the base year of 2016 for vehicles of model year MY (which have reached age $A = CY - MY$), $Population_{CY,A,S}$ is the number of vehicles of that age and body style 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 set equal to -0.085 (derived from Federal Highway Administration's (FHWA) U.S. LD VMT forecasting model).⁶¹⁶ Because both the adjusted value of annual VMT for vehicles of age A and the number of them in use ($Population_{CY,A,S}$) vary by regulatory alternative, the CAFE Model generates a slightly different estimate of NonReboundVMT during each future calendar year under each alternative; however, NHTSA omits the subscript corresponding to regulatory alternatives from Equation 4-12 for simplicity.

Before applying the rebound effect, NHTSA's analysis constrains each future year's VMT under all regulatory alternatives to match the VMT Constraint produced using the mileage accumulation schedules. It does so by adding or subtracting VMT from the provisional projection 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 non-rebound VMT derived from the baseline forecast and the estimate of total VMT obtained previously from Equation 4-12. That is:

Equation 4-13: Difference Between Total Vehicle Miles Traveled Constraint and Unadjusted Non-Rebound Total Vehicle Miles Traveled

$$\Delta Miles_{CY,Alt} = VMTConstraint_{CY} - NonReboundVMT_{CY,Alt}$$

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, 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

⁶¹⁶ FHWA's model predicts fleetwide travel demand based on macroeconomic factors. Since it cannot be used to predict travel for a subset of vehicles like the analysis fleet used in this rulemaking it is not suitable for the standard-setting analysis, though individual parameters from the model like its rebound elasticity are. For additional documentation see Pickrell, D. *et al.*, FHWA Travel Analysis Framework: Development of VMT Forecasting Models for Use by the FHWA, U.S. Department of Transportation, Volpe Center, pp. 1 – 19 (2020), available at: https://www.fhwa.dot.gov/policyinformation/tables/vmt/vmt_model_dev.pdf (accessed: May 22, 2026).

from the baseline simulation 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 a simple approach due to the lack of empirical evidence about how these additional miles would actually 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). 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.⁶¹⁷

The primary goal of reallocation is to show how CAFE standards influence the allocation of baseline travel across different vintages of vehicles in the on-road fleet through their effect on fleet turnover. It is important that any reallocation preserve the general pattern of declining average mileage with age displayed by 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 VMT Constraint. 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 MY 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 Total Vehicle Miles Traveled

$$R_{CY} = \frac{\Delta Miles_{CY}}{NonReboundVMT_{CY}}$$

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 Total Vehicle Miles Traveled

$$AdjNonReboundVMT_{CY} = \sum_A \sum_S^{Ages\ Styles} NonReboundVMT_{CY,A,S} * (1 + R_{CY})$$

⁶¹⁷ A notable exception to this is the impact of the COVID-19 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 forecast period.

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, NHTSA ensures 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 $\% \Delta NonRbdCPM$ calculated from Equation 4-11 and the elasticity of annual vehicle use with respect to fuel cost derived from the FHWA’s forecasting model for aggregate fleetwide VMT. 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 within the CAFE Model—most positive, but some potentially negative—over the course of their lifetime in the fleet.

4.3.4. Accounting for the Fuel-Economy Rebound Effect

The last step in the process of estimating the number of miles driven by vehicles of different ages is to account for the effect of higher fuel economy on vehicle use. The agency’s evaluation attributes all impacts of requiring higher fuel economy to 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 any such alternative. The processes for constraining and reallocating mileage 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 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. CAFE standards set at different levels will result in higher or lower fuel economy for new vehicles, thus changing the amount of fuel consumed driving each mile. The resulting difference in the cost to drive each mile will prompt a change in the number of miles new vehicles are driven, and this adjustment in vehicle use represents the fuel-economy rebound effect.

NHTSA recognizes the value of the rebound effect has an important influence on the costs and benefits associated with establishing 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 economy. NHTSA conducts an extensive review of recent estimates of the fuel-economy rebound effect, covering the past decade and spanning different geographic regions. This most recent survey includes all estimates of the rebound effect reported in each published study, while also recognizing the often-wide uncertainty surrounding these estimates. The agency reviews 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 mpg) 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 between vehicle use and vehicles’ fuel economy, while controlling separately for fuel prices. Because sources of external or independent variation in FE are rare and their average values for an entire vehicle fleet change very slowly over time, many analysts estimate the elasticity of vehicle use with respect to fuel cost per unit of distance driven instead (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 includes examples of published studies that rely on each of these strategies. Within each category, the survey identifies 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 4-19: 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 4-19 summarizes the details of studies of the rebound effect NHTSA included in its updated survey, and Table 4-20 identifies the individual studies and reports their locations, time periods they span, and type of data they utilize. The agency’s survey includes *all* estimates of the rebound effect reported in each published study, rather than a single “best” or most representative estimate. NHTSA weighs each published study equally, however, so that each individual value reported in a study that includes a large number of alternative estimates receives less weight than those from a study reporting a smaller number of estimates. To illustrate, each value from a study that reports ten separate estimates weighs only half as heavily as each value reported in a study that produces only five different estimates.

To recognize the statistical uncertainty surrounding each study’s findings, the agency combines its 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.⁶¹⁸ It then compiles these into summary probability distributions for different definitions of the rebound effect and the various data sources and analytic approaches used to estimate it.

Table 4-20: Details of Recent Studies

Authors (Date)	Nation	Time Period	Data	Range of Estimates
Greene (2010) ⁶¹⁹	U.S.	1966-2007	National aggregate VMT	0-13%
Wang <i>et al.</i> (2012)	Hong Kong	1993-2009	Year-to-year changes in nationwide driving	45%
Stapleton <i>et al.</i> (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 <i>et al.</i> (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 <i>et al.</i> (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 <i>et al.</i> (2017)	California	2009	3,500 households	1-18%
DeBorger (2016)	Denmark	2001-2011	23,000 households	5-12%
Andersson <i>et al.</i> (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%
Fronzel <i>et al.</i> (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 <i>et al.</i> (2015)	Pennsylvania	2000-2010	7 million vehicles	8-15%
West <i>et al.</i> (2015)	U.S.	2009	166,000 new vehicles	0%
Langer <i>et al.</i> (2017)	Ohio	2009-2013	229,000 driver-months	11-15%

⁶¹⁸ 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.

⁶¹⁹ Greene, D., Measuring Energy Security: Can the United States Achieve Oil Independence? Energy Policy, Vol. 38: pp. 1614-21 (2010), available at: <https://www.sciencedirect.com/science/article/pii/S0301421509000755> (accessed: May 22, 2026).

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 4-19 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 to 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, but at other times indicating the limited number of estimates they summarize. As Figure 4-19 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 household-based studies appear to fall into the 7-13-percent range, while analyses of the use of individual vehicles yield most likely values ranging from 12-13 percent.

Figure 4-19: Probability Distribution of Rebound Effect Estimates Based on Fuel Economy or Fuel Efficiency

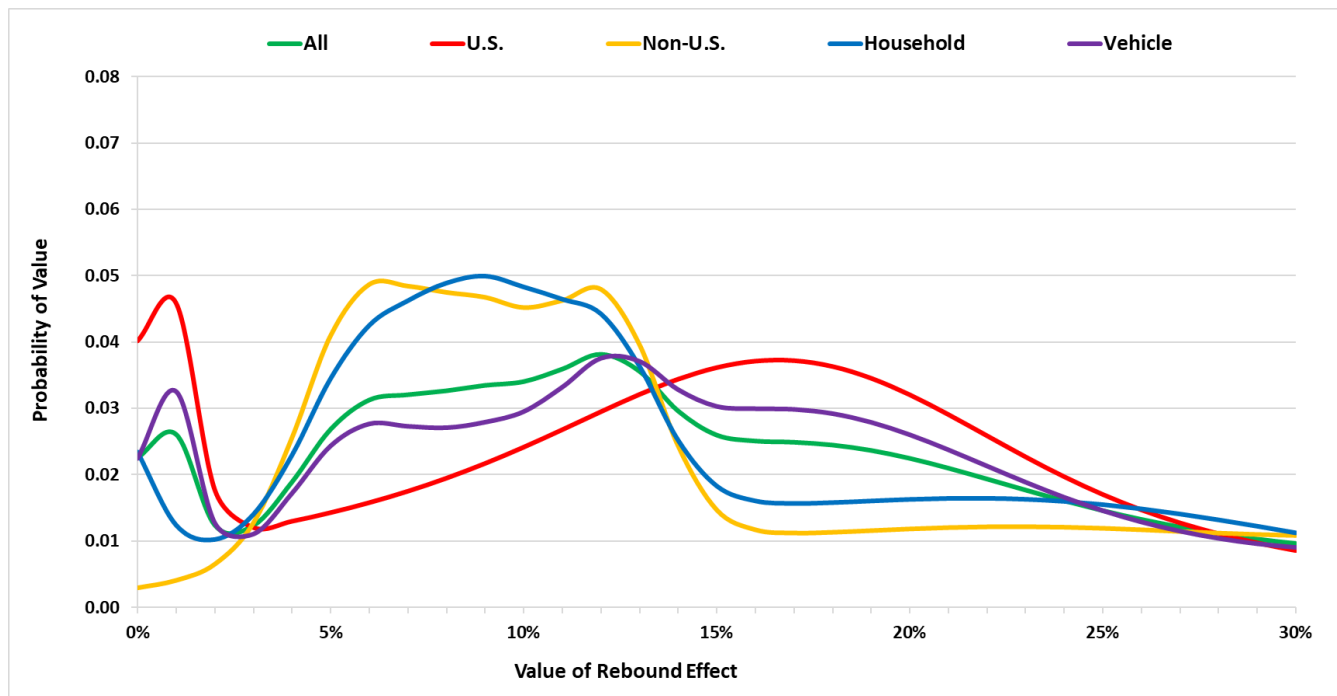
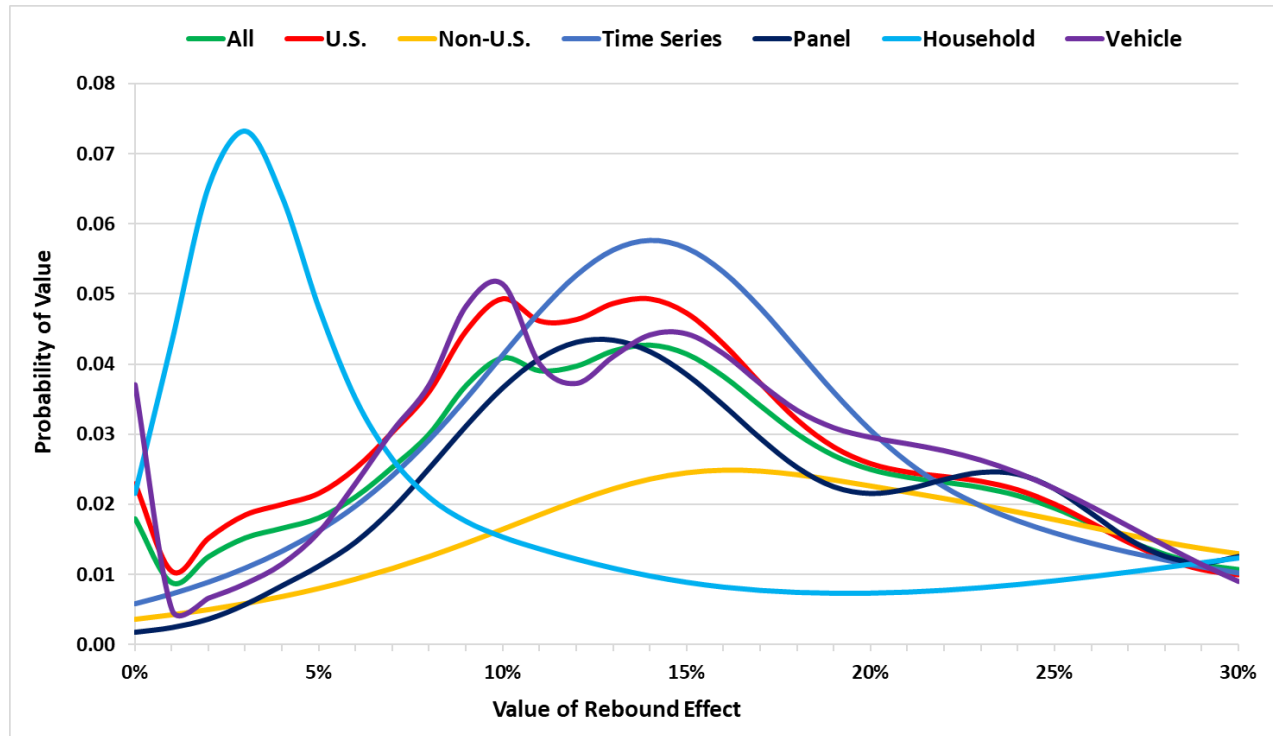


Figure 4-20 displays the probability distribution of estimates of the rebound effect derived from the elasticity of vehicle use with respect to fuel cost per unit of distance traveled. It incorporates results from 19 published studies reporting a total of 143 estimates, more than twice the number included in Figure 4-19. The two studies relying on household vehicle use suggest values for the rebound effect of less than 5 percent, while studies using other types of data and measurement approaches consistently indicate 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 4-20: Probability Distribution of Rebound Effect Estimates Based on Fuel Cost per Distance Traveled



It is also important to benchmark the findings from NHTSA’s analysis against previous large-scale surveys of published research on the rebound effect, and Table 4-21 summarizes the findings from four such surveys. In the earliest, Greening, Greene, and Difiglio (2000) reviewed 7 studies that estimated the rebound effect for LDVs 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.⁶²⁰

Sorrell (2007) subsequently reviewed 9 primarily European analyses and found considerably higher values; the studies based on FE 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 FE but a mean value less than half that (21 percent) for those based on fuel cost per km traveled.⁶²¹ For various reasons, those authors speculated that the lower end of the range they identified might be most appropriate.

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 FE (the authors’ preferred measure), and 20 percent when it is measured using variation in fuel cost per unit of distance

⁶²⁰ Greening, L. A. *et al.*, Energy Efficiency and Consumption—the Rebound Effect—A Survey, *Energy Policy*, Vol. 28 (6-7): pp. 389 – 401 (2000), available at: [https://doi.org/10.1016/S0301-4215\(00\)00021-5](https://doi.org/10.1016/S0301-4215(00)00021-5) (accessed: May 22, 2026).

⁶²¹ Sorrell, S. *et al.*, Empirical Estimates of the Direct Rebound Effect: A Review, *Energy Policy*, Vol. 37(4): pp. 1356 – 71 (2009), available at: <https://doi.org/10.1016/j.enpol.2008.11.026> (accessed: May 22, 2026).

traveled.⁶²² 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.⁶²³

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.⁶²⁴ 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.

Table 4-21: 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 <i>et al.</i> (2000)	7	–	–	–	–	13	20%	5%	31%	10-30%	–
Sorrell (2007)	9	4	40%	0%	87%	5	–	5%	30%	–	10-30%
Sorrell <i>et al.</i> (2009)	16	5	44%	0%	87%	12	21%	6%	32%	–	10-30%
Dimitropoulos <i>et al.</i> (2018)	69	203	27%	-64%	133%	445	20%	-28%	145%	~20%	26-29%

NHTSA’s assessment of the probability distributions presented here is that the median values of three of the five probability distributions shown in Figure 4-19 and of seven of the eight distributions shown in Figure 4-20 lie in the range of 10-15 percent, and occasionally even above 15 percent. In weighing the available evidence, NHTSA 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 economy or fuel CPM rather than the price of gasoline itself; and
- Estimates derived from more reliable data sources, such as DOT’s historical statistics on aggregate vehicle use or odometer readings for individual vehicles (*e.g.*, Gillingham *et al.* (2015), Knittel

⁶²² Dimitropoulos, A. *et al.*, The Rebound Effect in Road Transport: A Meta-Analysis of Empirical Studies, OECD Environment Working Papers, No. 113, 2016, OECD: Paris, France (2016), available at: https://www.oecd.org/content/dam/oecd/en/publications/reports/2016/12/the-rebound-effect-in-road-transport_e54dd56f/8516ab3a-en.pdf (accessed: May 22, 2026); see Table 5, at p. 25 (and accompanying discussion).

⁶²³ *Id.*, at p. 28.

⁶²⁴ *Id.*, at: pp. 163 – 79 (2018); see Table 4, at p. 170, Table 5, at p. 172 (and accompanying discussion), and Appendix B, Table B.V., at p. 177.

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 15 percent for this current analysis. This represents a difference from the 2024 final rule, when NHTSA used a value of 10 percent. While both values are plausible, 15 percent aligns more closely with the maximum of the probability distributions for U.S. estimates of the rebound effect based on CPM and fuel economy. Because the range of plausible values includes both smaller and larger values, NHTSA includes sensitivity analysis cases that use rebound effects of 10 percent and 20 percent. 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.

4.3.5. Total Vehicle Miles Traveled 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, 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. 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 MY 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's VMT 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 occur 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 Total Vehicle Miles Traveled with Rebound Miles

$$\text{ReboundVMT}_{\text{CY}} = \sum_A^{\text{Ages}} \sum_S^{\text{Styles}} \left(\frac{\text{VMT}_{\text{A,S}} \cdot (1 + \% \Delta \text{CPM}_{\text{MY,CY}} \cdot \epsilon_{\text{Rbd}}) + \Delta \text{Miles}_{\text{CY,A,S}} \cdot (1 + (\% \Delta \text{CPM}_{\text{MY,CY}} \cdot \epsilon_{\text{Rbd}} - \% \Delta \text{NonRbdCPM}_{\text{MY,CY}} \cdot \epsilon_{\text{FHWA}}))}{\text{Population}_{\text{CY,A,S}}} \right)$$

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. 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 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 estimates of rebound mileage 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 variation in rebound-effect driving will contribute relatively more to the economic and safety impacts in the analysis.

5. Simulating Emissions Impacts of Regulatory Alternatives

This final rule sets standards for fuel economy, which affects fuel consumption in the United States. Fuel economy standards impact vehicle exhaust emissions during operation as well as upstream emissions during petroleum extraction, transportation, refining, and fuel transportation, storage, and distribution (TS&D). This chapter includes a discussion on the development and evolution of input parameters used to estimate emissions of criteria pollutants, certain gases (CO₂, CH₄, N₂O), and air toxics.

The final rule implements an emissions inventory methodology for estimating impacts. Vehicle emissions inventories are described as using three metrics, comprising activity (*e.g.*, miles traveled, hours operated, or gallons of fuel burned), population (or number of vehicles), and EFs. An EF is a representative rate that attempts to relate the quantity of a pollutant released to the atmosphere per unit of activity.

Upstream EFs are applied on a fuel volume basis, and downstream EFs are applied on a distance-traveled basis.

The final rule’s upstream emission inventory is the product of the per-gallon EF and the corresponding number of gallons of gasoline or diesel consumed. Similarly, the downstream emission inventory is the product of the per-mile EF and the appropriate miles traveled estimate. The only exceptions are that vehicle-based sulfur oxides (SO_x) and CO₂ also use a per-gallon EF in the CAFE Model. The activity levels—both miles traveled and fuel consumption—are generated by the CAFE Model, while the EFs have been incorporated from other models used by Federal agencies.

Downstream and upstream EFs and subsequent inventories were developed independently from separate data sources. Upstream EFs are estimated from a life-cycle emissions model developed by Argonne. Downstream EFs are estimated from the regulatory highway emissions inventory model developed by the EPA National Vehicle and Fuel Emissions Laboratory. Data from the latest EPA and DOE models are utilized to update the CAFE Model.

This chapter also details NHTSA’s estimate of how criteria pollutant emissions could affect human health. Further description of how the health impacts of upstream and downstream criteria pollutant emissions can vary and how these criteria pollutant emission damages are monetized and incorporated into the final rule can be found in Final TSD Chapter 6.2.

5.1. Activity Levels Used to Calculate Emissions Impacts

Emission inventories in this final 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. 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 number remaining in service in each calendar year, as well as the annual mileage accumulated (*i.e.*,

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

VMT) at each age. Inventories by model year are derived from the annual mileage and corresponding EFs.

As discussed in Final TSD Chapter 2.1, for each vehicle model/configuration in each model year from MY 2024 to MY 2050 for upstream estimates and MY 2060 for downstream estimates, the CAFE Model estimates and records the fuel type (*e.g.*, gasoline or diesel), fuel economy, and number of units sold in the United States. The CAFE Model uses an aggregated representation of vehicles sold in the United States during 1985-2024. 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. Based on estimates of fleetwide annual VMT for cars and light trucks in service each calendar year spanned by this analysis, the Model calculates the quantities of each type of fuel or energy consumed in each calendar year. By combining these with estimates of each model's fuel or energy efficiency, the model 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.

Final TSD Chapters 4.2 and 4.3 describe in detail 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, the procedures used to combine these into estimates of annual fleetwide travel during each future calendar year, and the sources of estimates for survival rates and average use at each age. The data and procedures the CAFE Model employs to convert these estimates of VMT to fuel and energy consumption by individual model, and aggregate the results to calculate total consumption and energy content of each fuel type during future calendar years, are described in detail in Final TSD Chapters 4.2 and 4.3.

The CAFE Model Documentation accompanying this final rule describes these procedures in detail. The Model calculates emissions based on a set of “activity levels,” which are quantities of travel and fuel consumption estimated for the cross section of model years and calendar years. The Model does so by multiplying activity levels by EFs. The resulting estimates of vehicle use (*i.e.*, VMT), fuel consumption, and fuel energy content are combined with EFs drawn from various sources to estimate emissions of CO₂, CH₄, N₂O, 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. EFs measure the mass of each gas 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 EFs 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 gas, criteria pollutant, and airborne toxic compound.

5.2. Simulating Upstream Emissions Impacts

The analysis considers the effects of both downstream and upstream emissions. Consistent with past CAFE analyses, this rule uses upstream EFs from the GREET Model.⁶²⁵ For this final rule, upstream emissions for gasoline, diesel, and electricity fuel types have been updated using GREET 2025, integrated with the electricity grid mix projections from the AEO 2026 Alternative Electricity and Transportation scenario.⁶²⁶ These updates generally resulted in higher upstream EFs for all pollutants and fuel types.

⁶²⁵ Argonne National Laboratory, The Research and Development Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies (R&D GREET) Model 2025 (2025), last revised: Dec. 2025, available at: <https://greet.anl.gov/> (accessed: May 22, 2026).

⁶²⁶ Projections are taken from the AEO 2026 Alternate Transportation and Electricity Case Table 8 and Table 16, available at: https://www.eia.gov/outlooks/aeo/tables_side.xls.php (accessed: May 22, 2026).

This chapter describes how the agency calculated these updated upstream EFs in grams/million British Thermal Units (mmBTU) for the following emissions:

Criteria pollutants

- CO,
- VOCs,
- NO_x,
- SO_x, and
- PM_{2.5};

Non-criteria pollutants

- CO₂,
- CH₄, and
- nitrous oxide (N₂O).

EFs for air toxics and PM of 10 µm or less (PM₁₀) remain unchanged from previous CAFE rules.

For each analysis year, the EFs for the four upstream emission processes for gasoline and diesel include: petroleum extraction, petroleum transportation, petroleum refining, and fuel TS&D.

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 the following 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. The petroleum extraction calculation begins by summing all the EFs by extraction subprocess from the GREET 2025 Petroleum tab. For example, the 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, coproduced electricity credit, flaring emissions, and non-combustion emissions from the extraction and separation of bitumen.

Each extraction EF is multiplied by the associated loss factors and energy share for each combination of feedstock and primary extraction process. The loss factors represent the process inefficiencies of transport to U.S. refineries and of storage, while the energy share is the proportion of total energy content supplied to U.S. refineries by each type of crude feedstock. These 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 energy share of each feedstock, and EF of each pollutant, varies by analysis year.

For every year in the series of analysis years, and for every pollutant in the full set of pollutants 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 United States (also found in the GREET Petroleum tab), or one minus the pure ethanol energy content. The final diesel EF is assumed to have no ethanol content.

There are a few notable exceptions to this approach for pollutants that GREET originally separates by their sources and later combines in the extraction calculation. Many extraction processes do not include *VOC from bulk terminal* and *CH₄: non-combustion* but are added to primary VOC and CH₄ estimates

respectively for crude oil and shale oil recovery. The petroleum transportation and fuel TS&D processes also consider combined VOC and CH₄ EFs.

5.2.2. Petroleum Transportation

The petroleum transportation process only includes the transport processes of crude feedstocks sent for domestic refining and omits the loss factors by crude feedstock. As with petroleum extraction, the petroleum transportation EF is aggregated by feedstock/process combinations also located in the GREET 2025 Petroleum tab.

As in the extraction process calculation, the crude feedstock transportation EFs are generated for each fuel type, year in the series of analysis years, and each pollutant in the full set of pollutants. The final petroleum transportation EF for gasoline is multiplied by the national default non-ethanol remainder, whereas the final transport EF for diesel does not contain any ethanol.

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 CH₄ comprises 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 2025, the refining processes are found in the finished gasoline and low-sulfur diesel subchapters of the Petroleum tab.

Because 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 EF calculation while the energy share is not.

In 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 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.

In the refining calculations, there are no exceptions for VOC or CH₄. Both primary VOC and CH₄ combustion account for the total VOC and total CH₄, respectively.

5.2.4. Fuel Transportation, Storage, and Distribution

The final upstream process after refining is 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 EFs 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.

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 2025 is the reported EFs for E0 blendstock transportation and distribution.

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 (ethanol) tab, where the total ethanol EF is the sum of its fuel and feedstock subprocesses.

Total CH₄ for fuel TS&D is based solely on the *CH₄: combustion* component and total VOC is the sum of the primary VOC and other components from the TS&D process. However, for the gasoline TS&D calculation in GREET 2025, 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 in earlier rulemakings. While the 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. In addition, NHTSA has updated the CAFE Model to calculate these upstream emission rates separately for the domestic and global segments of the fuel supply chain, consistent with the latest recommended Circular A-4.⁶²⁷ This update applies to both criteria and non-criteria emissions to ensure consistency across pollutants.⁶²⁸

To calculate domestic emission volumes, the CAFE Model aggregation method differs from the GREET method and considers the following two upstream adjustments for CAFE:

- Share of fuel savings leading to reduced domestic fuel refining, and
- Share of reduced domestic refining from domestic crude.⁶²⁹

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 each year in the series of analysis years and each pollutant in the full set of pollutants. Global emission estimates do not apply these share adjustments.⁶³⁰

For consistency, these aggregated gasoline and diesel *EF* calculations occur in the CAFE Model rather than the processing script or elsewhere. Upstream adjustments in the CAFE Model are constant across fuel types, analysis years, and are constant within each group of pollutants.

5.3. Simulating Downstream Emissions Impacts

Downstream EFs are generated using the latest regulatory model for on-road emission inventories from the EPA, the MOVES5. This subchapter is broken into two primary components: (1) preparing model runs to estimate vehicle-based emission inventories and vehicle activity, referred to below as pre-processing and (2) calculating vehicle-based EFs on a per-mile basis, referred to below as post-processing. In addition, this subchapter discusses the separate process for generating vehicle-based CO₂ emissions levels in the CAFE Model.

⁶²⁷ Circular A-4, Regulatory Analysis, *Federal Register*, October 9, 2003, available at: <https://www.federalregister.gov/documents/2003/10/09/03-25606/circular-a-4-regulatory-analysis> (accessed: May 21, 2026).

⁶²⁸ For further discussion, see preamble Section II.F.

⁶²⁹ See Chapter 6.2.4.3 for further discussion about NHTSA's import assumptions.

⁶³⁰ For more detail on this calculation, see the CAFE Model Documentation and MOVES5 Docket Memo.

5.3.1. Pre-Processing of Motor Vehicle Emission Simulator Data

The CAFE Model’s vehicle-based input parameters for criteria pollutants, CH₄, N₂O, and mobile-source air toxics are updated using the most recent version of MOVES5, released in November 2024. MOVES5 is a state-of-the-science, mobile-source emissions inventory model for regulatory applications.⁶³¹ New MOVES5 vehicle-based EFs are incorporated into the CAFE parameters, and these updates supersede previous MOVES downstream data.

Since the release of the 2025 NPRM, EPA has rescinded the 2009 Greenhouse Gas Endangerment Finding.⁶³² Consequently, the standards regarding CO₂, CH₄, and N₂O promulgated through the 2023-2026 Light-Duty Greenhouse Gas Rule and 2027 Multi-Pollutant Rule have been repealed. These rules required future reductions in vehicle emissions of CO₂, CO, CH₄, NO_x, and PM_{2.5}, and were accounted for in MOVES5 baseline emission rates. For this final rule, the impacts of EPA’s rules on downstream CH₄, N₂O, and CO₂ emission factors have been removed. With the exception of CO₂, this was done by replacing baseline emission rates in MOVES5 with those used in MOVES4 for the affected pollutants and vehicle model years, fuel types, and regulatory classes, as these values more accurately reflect current regulatory requirements. For CO₂ only, an additional adjustment was applied to the MOVES4 baseline energy consumption rates for model years, fuel types, and regulatory classes affected by the 2023-2026 Light-Duty Greenhouse Gas Rule. As of this rulemaking, criteria pollutant standards set forth by the aforementioned EPA rules remain unchanged; therefore, MOVES5 emission rates for these pollutants were not adjusted from the NPRM.

A national-scale MOVES5 run specification file is developed for each model year,⁶³³ with inputs limited to fuel types, pollutants, and vehicle classes relevant to this rulemaking. Beyond designating 1 year per run, each run is performed with the same run specifications and performed hourly to include evaporative processes, but EFs are aggregated and are reported on an annual basis. Downstream parameters in the CAFE Model maintain their format and extend to MY 2060.⁶³⁴

5.3.2. Post-Processing of MOVES Data

The MOVES5 data are post-processed into input parameters for the CAFE Model using a script for automation. Downstream emission parameters are updated for gasoline and diesel LDVs and trucks, including the criteria pollutants, CO₂, CH₄, N₂O, and air toxics across MYs 1984-2060. MOVES5 runs create individual output databases for each of the 63 evaluation years for which run specifications are generated. Output databases contain 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 MOVES5.

5.3.2.1. Description of MOVES Output Tables and Data Manipulation

While the MOVES output database contains many tables, only two are necessary to estimate downstream emissions: movesoutput and movesactivityoutput.

⁶³¹ EPA, Motor Vehicle Emission Simulator: MOVES5, Office of Transportation and Air Quality, last revised: Nov, 2025, available at: <https://www.epa.gov/moves/latest-version-motor-vehicle-emission-simulator-moves> (accessed: Apr 20, 2026).

⁶³² EPA, Final Rule: Rescission of the Greenhouse Gas Endangerment Finding and Motor Vehicle Greenhouse Gas Emission Standards Under the Clean Air Act, last revised Feb. 2026, available at: <https://www.epa.gov/regulations-emissions-vehicles-and-engines/final-rule-rescission-greenhouse-gas-endangerment> (accessed: May 21, 2026).

⁶³³ A MOVES5 run specification for CY 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.

⁶³⁴ For a detailed list of MOVES5 run specifications, see Docket Memo for MOVES5 runs Docket ID.

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 are used in a post-processing script:

movesoutput: *yearID*, *modelYearID*, *regClassID*, *fuelTypeID*, *pollutantID*,
emissionQuant

movesactivityoutput: *yearID*, *modelYearID*, *regClassID*, *fuelTypeID*, *activity*

These data are then used to compute Age, VMT, and emissionRate, where:

Age is the difference between *modelYearID* and *yearID*

VMT is the sum of distance traveled, grouped by *yearID*, *modelYearID*,
pollutantID, and *regClassID* for gasoline and diesel separately

emissionRate is the aggregated emissions inventories divided by the aggregated
VMT.

The MOVES5 output does not cover all model years and ages required by the CAFE Model. MOVES5 only generates emissions data for vehicles made in the last 40 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 with available emissions data and forward fills the data as a constant value for the subsequent vehicle ages.

Finally, to ensure the Parameters Input File is modified correctly, NHTSA conducts quality assurance tests, which include checking the accuracy of previous emission parameters.

5.3.3. Simulating Downstream CO₂ and SO_x Emissions

Much like the input parameters for criteria pollutant emissions, the CAFE Model input parameters for CO₂, CH₄, and N₂O are generally taken from other models. Upstream EFs come from GREET 2025, and downstream, CH₄, and N₂O EFs come from MOVES5. This subchapter briefly describes the methodology for the development and use of the vehicle-based CO₂ and SO_x EFs.

5.3.3.1. CO₂ Emissions

For vehicle-based CO₂ 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 EFs associated with each fuel, the carbon content is multiplied by the mass density of a particular fuel as well as by the ratio of the molecular weight of CO₂ to that of elemental carbon (EC). This ratio, a constant value of 44/12, measures the mass of CO₂ produced by the complete combustion of the mass of carbon contained in each unit of fuel. The resulting value defines the EF attributed to CO₂ as the number of grams of CO₂ emitted during vehicle operation from each type of fuel. This calculation is repeated for gasoline and diesel fuel types and defined in grams per gallon of the given fuel source.

5.3.3.2. SO_x Emissions

Sulfur dioxide (SO₂) and other SO_x are some of the most harmful criteria pollutants to human health but have been dwindling recently in the United States 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 been reduced.^{635,636} There is a strong correlation between the fuel sulfur content and the SO_x emitted. The CAFE Model utilizes SO_x EFs based on the energy content (mmBTU) of the fuel consumed.

SO_x is estimated directly from EPA’s MOVES5 release, but SO_x EFs are based on fuel consumption instead of VMT. MOVES5 estimates only SO₂ but all SO_x emissions are represented as SO_x.^{637,638} This is because SO₂ constitutes 95 percent or more of SO_x in combustion and the CAFE Model’s upstream emissions are reported as SO_x. Since MOVES5 predicts that SO_x EFs (in grams per mmBTU) remain unchanged after 2022, this analysis assumes constant SO_x rates by fuel type.

5.3.3.3. Summary of CAFE Fuel Properties

The table below summarizes the mass density, carbon content, CO₂, and SO_x EFs for gasoline and diesel fuel types.

Table 5-1: CO₂ and SO_x Emission Factors by Fuel Type

Fuel Type	Mass Density (grams/unit)	Carbon Content (% by weight)	CO ₂ Emission Factor (grams/unit)	SO _x Emissions (grams/MMBTU)
Gasoline (gallons)	2,823	85.9%	8,887	0.364
Low-Sulfur Diesel (gallons)	3,206	86.6%	10,180	0.262

For the surviving on-road fleet, the CAFE Model calculates CO₂ vehicle-based emissions associated with vehicle operation by multiplying the number of gallons of a specific fuel consumed by the CO₂ EF for the associated fuel type. Specifically, the number of gallons of a particular fuel is multiplied by the carbon content and the mass density per unit of that fuel type. Then, the ratio of CO₂ emissions generated per unit of carbon consumed during the combustion process is applied.⁶³⁹

5.3.3.4. Emissions from Brake and Tire Wear

Particles from BTW are becoming an increasingly significant component of PM emission inventories as PM from vehicle exhaust decreases due to longstanding air quality regulations. This final rule considers PM_{2.5} from the vehicle’s exhaust, brakes, and tires.

BTW estimates are modeled using MOVES5. The latest version of MOVES5 incorporates an updated approach to modelling brake wear EFs, but the method for estimating tire wear EFs remains unchanged.

Because of new brake wear test data, assumptions about brake pad composition and vehicle mass by fuel source type are changed for MY 2011 and later. Most notably, MY 2011 and later vehicles present with

⁶³⁵ DieselNet, Fuel Regulations, last revised: Dec. 2009, available at: <https://dieselnet.com/standards/us/fuel.php> (accessed: May 13, 2026).

⁶³⁶ EPA, Gasoline Sulfur, last revised: Feb. 10, 2023, available at: <https://www.epa.gov/gasoline-standards/gasoline-sulfur> (accessed: May 13, 2026).

⁶³⁷ Trijonis, J., Air Quality and Stationary Source Emission Control, Washington, D.C.: National Academies Press, p. 233 (1975), available at: <https://nap.nationalacademies.org/read/10840/chapter/8> (accessed: May 13, 2026).

⁶³⁸ CIMAC, Guide to Diesel Exhaust Emissions Control of NO_x, SO_x, Particulates, Smoke, and CO₂: Seagoing Ships and Large Stationary Diesel Power Plants, Conseil International des Machines à Combustion (CIMAC): Frankfurt/Main, Germany, p. 12 (2008), available at: https://www.cimac.com/cms/upload/Publication_Press/Recommendations/Recommendation_28.pdf (accessed: May 13, 2026).

⁶³⁹ Chapter 3, Section 4 of the CAFE Model Documentation provides an additional description for calculation of CO₂ vehicle-based emissions with the Model.

lower brake wear EFs than pre-2011 model year vehicles.^{640,641} To capture this variation in the CAFE Model, BTW inputs are differentiated by regulatory class, fuel type, and model year group classification (pre-2011 and 2011+). Vehicle model years before MY 2011 have identical values for gasoline and diesel. Unlike the CAFE Model’s powertrain-associated EFs, the BTW estimates are averaged over all model years and ages (in each of the model year group classifications) in grams per mile, as summarized in Table 5-2.

Table 5-2: CAFE Model Brake and Tire Wear Emissions Assumptions

Model Year	Fuel Type	PM _{2.5} Brake Wear (g/mi)		PM _{2.5} Tire Wear (g/mi)	
		LDV	LDT*1/2a	LDV	LDT1/2a
Pre-2011	Gasoline	0.0031	0.0031	0.0013	0.0013
Pre-2011	Diesel	0.0031	0.0031	0.0013	0.0013
2011+	Gasoline	0.0022	0.0026	0.0013	0.0013
2011+	Diesel	0.0023	0.0031	0.0013	0.0013

* LTD is Light-Duty Trucks.

In a fuel cycle or well-to-wheel (WTW) analysis, powertrain emissions and BTW emissions together are referred to as the tank-to-wheel (TTW) portion. To compute PM_{2.5} TTW emissions for a gasoline or diesel LDV in the CAFE Model, the tailpipe (TP) emissions for a given vehicle regulatory class, model year, and age, are added to the corresponding brake wear (BW) and tire wear (TW) for a vehicle of that regulatory class.

The following visualizations of BTW EFs by regulatory class and fuel type illustrate trends in these measures over time. EFs are presented in levels Figure 5-1 and as a percentage of the total Figure 5-2. For both passenger cars and light trucks, BTW particulate constitutes a slight majority of PM_{2.5} emissions by 2035. Brake wear from cars and light trucks accounts for up to 50 percent of their PM_{2.5} inventories by 2050.

⁶⁴⁰ The estimated reduction in brake wear EFs for vehicles MY 2011 and beyond assumes that 82 percent of brakes are made with non-asbestos organic material and 18 percent with low-metallic material; no brake pads are assumed to be made of semi-metallic material. Brake wear EFs for model years prior to MY 2011 assume an even distribution in the use of non-asbestos organic, low-metallic, and semi-metallic brake pads.

⁶⁴¹ EPA, Brake and Tire Wear Emissions from Onroad Vehicles in MOVES5, EPA-420-R-24-012, EPA: Washington, D.C., pp. 1 – 69 (2024), available at: <https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockkey=P101CTUW.pdf> (accessed: May 13, 2026).

Figure 5-1: CAFE Gasoline PM_{2.5} Emission Factors Over Time by Vehicle Regulatory Class and Source

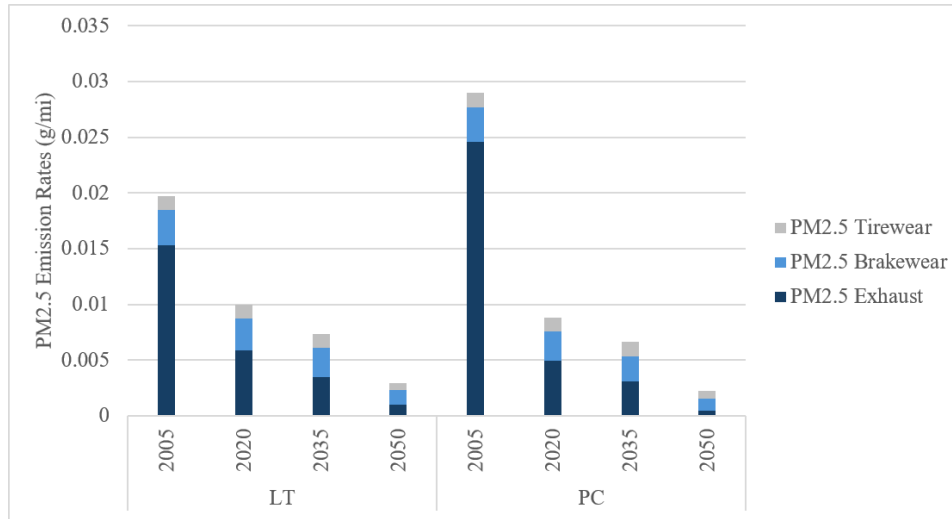
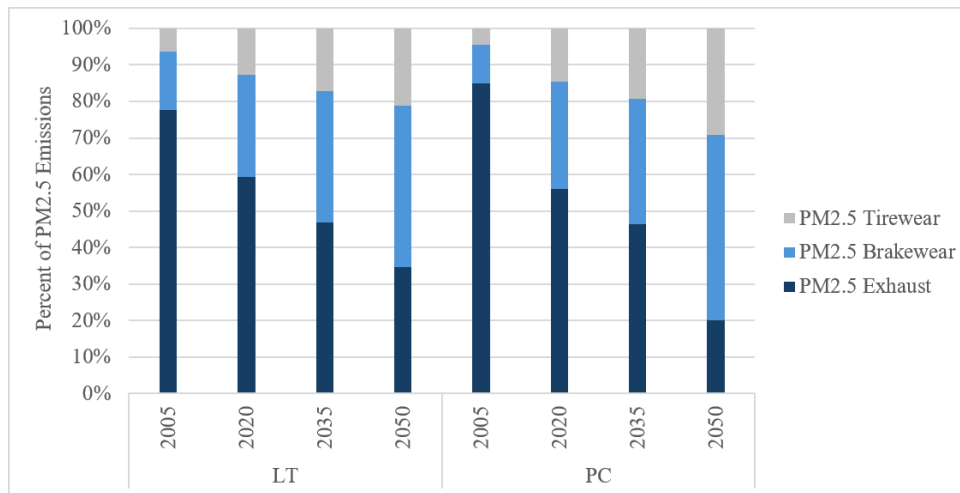


Figure 5-2: CAFE Gasoline Emission Parameters for PM_{2.5} as a Percentage of Total Emissions by Regulatory Class, Source, and Evaluation Year



The next subchapter describes the adverse human health impacts from both upstream and downstream vehicle emissions and NHTSA’s approach to quantifying them.

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 PM and two precursors to PM_{2.5} (NO_x and SO_x). These health impacts include several different morbidity measures, as well as mortality estimates, and are measured by the number of instances predicted to occur per ton of each PM_{2.5}-related pollutant emitted (direct PM as well as NO_x and SO_x, both precursors to PM_{2.5}, which is formed secondarily). The CAFE Model reports total PM_{2.5}-related health impacts by multiplying the estimated tons of each PM_{2.5}-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 PM_{2.5}-related pollutants are described in Chapter 5.2. This subchapter discusses how the health incidence per ton values are obtained. See Chapter 6.2.2 Monetized

Health Impacts from Changes in Criteria Pollutant Emissions for information regarding the monetized damages arising from these PM_{2.5}-related health impacts.

5.4.1. Health Impacts per Ton from Upstream Emissions

This subchapter describes the values for health incidence per ton used to calculate the total health impacts from upstream criteria pollutant emissions. The values for health incidence per ton reflect the differences in health impacts arising from five upstream emission source sectors (petroleum extraction, petroleum transportation, refineries, fuel transportation, storage and distribution, and for the Final SEIS analysis, electricity generation), based on publicly available EPA reports that appropriately correspond to these sectors.⁶⁴² Within the pollutant categories listed above, the differences in the incidence per ton values across different years arise from differences in the geographic distribution of the pollutants, a factor that affects the number of people impacted by the pollutants.⁶⁴³

The CAFE Model health impacts inputs are based partially on the structure of EPA’s 2018 TSD, *Estimating the Benefit per Ton of Reducing PM_{2.5} Precursors from 17 Sectors* (referred to here as the 2018 EPA source apportionment TSD).⁶⁴⁴ 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 mortality and morbidity) that are expected from reducing one ton of directly emitted PM_{2.5} or PM_{2.5} precursor, such as NO_x or SO_x. The complex, non-linear photochemical processes that govern ozone formation prevent the agency 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. NHTSA includes additional discussion of uncertainties in the BPT approach in Chapter 5.4.2.

Though EPA published an updated health impact per ton values for various sectors, including refineries, oil and gas, and electricity-generating units (*Estimating the Benefit per Ton of Reducing Directly-Emitted PM_{2.5}, PM_{2.5} Precursors and Ozone Precursors from 21 Sectors*), NHTSA does not use these because the new estimates are not available for all sectors.⁶⁴⁵ Switching to the values that use the latest EPA methodology at this time requires leaving out multiple relevant pollutant sectors from NHTSA’s analysis (petroleum transportation, TS&D, and mobile source sectors). While the older health incidence values in the analysis are lower than the newer values, and slightly undervalue the benefits of reducing health emissions, removing these categories would 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 years 2016 and 2020 are not included in this analysis, the 2016 and 2020 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, 2025 values are applied for 2024-2027, and 2030 values are applied for the years after 2027. The CAFE Model Documentation contains additional details and 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

⁶⁴² For further discussion of the EPA reports used for each upstream emissions source sector, see preamble Section II.F.

⁶⁴³ Office of Air and Radiation and Office of Air Quality Planning and Standards, pp. 1 – 108 (2018).

⁶⁴⁴ *Id.*, at pp. 1 – 108.

⁶⁴⁵ *Id.*, at pp. 1 – 50.

sources based on newer air quality modeling updates leads to the use of multiple papers. Table 5-3 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.⁶⁴⁶ DOT staff examines how each component is defined in GREET 2025 to map EPA source sectors to the ones used in the CAFE Model.

Table 5-3: 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 <i>et al.</i>). ⁶⁴⁷ 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 <i>et al.</i>). ⁶⁴⁸ and one source sector from the 2018 EPA source apportionment TSD. ⁶⁴⁹ The specific mode mappings are as follows: From Wolfe <i>et al.</i> : 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.
Fuel TS&D	Assigned to several mobile source sectors from a 2019 EPA paper (Wolfe <i>et al.</i>) and one source sector from the 2018 EPA source apportionment TSD. ⁶⁵⁰ The specific mode mappings are as follows: From Wolfe <i>et al.</i> : 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.

⁶⁴⁶ Argonne National Laboratory (2025).

⁶⁴⁷ Fann *et al.*, Assessing Human Health PM_{2.5} and Ozone Impacts from U.S. Oil and Natural Gas Sector Emissions in 2025, *Environmental Science & Technology*, Vol. 52(15): pp. 8095 – 103 (2018), available at: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6718951/> (accessed: May 13, 2026) (hereinafter, “Fann *et al.* (2018)”).

⁶⁴⁸ Wolf *et al.*, Monetized Health Benefits Attributable to Mobile Source Emission Reductions Across the United States in 2025, *Science of the Total Environment*, Vol. 650(2): pp. 2490 – 98 (2019), available at: <https://doi.org/10.1016/j.scitotenv.2018.09.273> (accessed: May 13, 2026) (hereinafter, “Wolfe *et al.* (2019)”). Health incidence per ton values corresponding to this paper were sent by EPA staff.

⁶⁴⁹ Office of Air Quality Planning and Standards, 2018., A, pp. 1 – 108.

⁶⁵⁰ *Id.*, at pp. 1-108.

5.4.1.1. Health Incidence per Ton Values Associated with the Petroleum Extraction Sector

Health impacts from the petroleum extraction sector are based on a 2018 oil and natural gas sector paper (Fann *et al.*), which estimates health impacts for this sector in the year 2025.⁶⁵¹ This paper defines the oil and gas sector’s emissions not only as arising from petroleum extraction, but also from transportation to refineries. In contrast, the CAFE/GREET component is composed of only petroleum extraction. NHTSA has concluded that the estimates from the 2018 paper are appropriate estimates for the petroleum extraction sector.

Specific health incidences per pollutant are not reported in the paper, so EPA provided BenMAP Health Incidence Files for the oil and natural gas sector upon request. NHTSA calculates per ton values based on these files and the tons reported in the Fann *et al.* paper.⁶⁵²

The only available health impacts correspond to the year 2025. Rather than trying to extrapolate, these 2025 values are used for both of the relevant years in the CAFE Model structure, 2025 and 2030.⁶⁵³

NHTSA understands that uncertainty exists around the contribution of VOCs to PM_{2.5} formation in the modeled health impacts from the petroleum extraction sector; however, NHTSA believes 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.

5.4.1.2. Health Incidence per Ton Values Associated with the Petroleum Transportation Sector

The petroleum transportation sector does not correspond to any of the EPA source sectors, so a weighted average of multiple different EPA sectors is used to determine the health impact per ton values for the petroleum transportation sector as a whole. In calculating the weighted average, DOT maps the petroleum transportation sector as described in GREET to a combination of different EPA mobile source sectors from two different papers. These papers include the 2018 EPA source apportionment TSD,⁶⁵⁴ and a 2019 mobile source sectors paper (Wolfe *et al.*).⁶⁵⁵

Wolfe *et al.* includes 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; in consultation with EPA, DOT applies these values to the other years in the input structure.

⁶⁵¹ Fann *et al.* (2018).

⁶⁵² 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.* 2018 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}.

⁶⁵³ These 3 years are used in the CAFE Model structure because it was originally based on the estimate provided in the 2018 EPA source apportionment TSD.

⁶⁵⁴ Office of Air Quality Planning and Standards, pp. 1 – 108 (2018).

⁶⁵⁵ Wolfe *et al.* (2019).

A weighted average of these different sectors is used to calculate the total health incidences per ton by pollutant, based on the percent of upstream emissions attributable to each transportation mode.

The GREET model informs the CAFE upstream component categories. There are five types of petroleum products relevant to upstream emissions for gasoline:

- Conventional crude oil
- Synthetic crude oil (SCO)
- Dilbit
- Shale oil (Bakken)
- Shale oil (Eagle Ford)

Table 5-4: Petroleum Transportation Mode Shares in 2025⁶⁵⁶

Fuel Type ⁶⁵⁷	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 5-4. Transportation both within 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 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 5-5, 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. In addition, 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,

⁶⁵⁶ These values are from the GREET 2025 model, using reference year 2025. In the Excel version, this information can be found in the T&D Flowcharts worksheet. See <https://greet.anl.gov/> to download the model.

⁶⁵⁷ Conventional crude oil is both extracted both 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.

different weights are used for years 2025 and 2030, based on the mode percentages GREET reports for those years.⁶⁵⁸

Table 5-5: Energy Share by Petroleum Type⁶⁵⁹

Conventional Crude Oil	SCO	Dilbit	Shale (Bakken)	Shale (Eagle Ford)
79.1%	3.5%	5%	6.5%	5.9%

NHTSA multiplies the energy share of each petroleum type by its corresponding emissions value to reflect how much of each emissions value go into the weighted average. For example, using the energy share information in Table 5-5, the conventional crude emissions are multiplied by 79.1 percent, SCO emissions are multiplied by 3.5 percent, Dilbit emissions are multiplied by 5 percent, shale (Bakken) emissions are multiplied by 6.5 percent, and shale (Eagle Ford) emissions are multiplied by 5.9 percent.

NHTSA sums the resulting weighted emissions values by pollutant to represent the total upstream emissions in grams/mmBTU of petroleum product transported. With that information, NHTSA calculates the percentages of each pollutant attributable to each mode for petroleum transportation overall. These calculations are completed for each different base year (2025 and 2030). Table 5-6 shows these percentages, using base year 2025 as an example.

Table 5-6: Percent of Emissions Attributable to Each Mode for the Petroleum Transportation Category⁶⁶⁰

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 5-1 illustrates this process. The variables beginning with “%” represent the percent of SO_x emissions 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 5-1: Weighted Average of Health Incidences from the Petroleum Transportation Sector

Asthma Exacerbation incidents per ton from SO_x in Petroleum Transportation=

$$(\% \text{ SO}_x \text{ ocean tanker} * C3\text{marine}) + (\% \text{ SO}_x \text{ barge} * C1\&C2 \text{ marine})$$

⁶⁵⁸ These are the 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.

⁶⁵⁹ Taken from the Petroleum tab of the GREET Excel model, using 2025 as a base year.

⁶⁶⁰ These percentages are calculated using the 2025 base year in GREET.

$$+ (\%SO_x \text{ pipeline} * EGU) + (\% SO_x \text{ rail} * Rail) + (\% SO_x \text{ truck} * Truck)$$

Following guidance from the 2018 EPA source apportionment TSD, NHTSA rounds the incidence per ton values to two significant digits.⁶⁶¹

5.4.1.3. Health Incidence per Ton Values Associated with the Fuel Transportation, Storage, and Distribution Sector

Like the petroleum transportation sector, the fuel TS&D sector corresponds to several different EPA source sectors. DOT uses 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 maps these components to five different transportation source sectors from two EPA papers (the 2018 EPA source apportionment TSD and the 2019 mobile sources paper).⁶⁶²

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. For instance, on the last leg of their trip, 100 percent of gasoline blendstocks are transported by trucks within the United States. As an example, Table 5-7 shows the estimated mode shares in 2025.

Table 5-7: Transportation Mode Shares for the Fuel TS&D Sector⁶⁶³

Mode Share	Gasoline Blendstocks	Finished Gasoline
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 is calculated to find the percentage of emissions attributable to each mode for fuel TS&D overall. Table 5-8 provides an example of these percentages.

Table 5-8: Percent of Emissions Attributable to Each Mode for the Fuel TS&D Sector⁶⁶⁴

Mode	EPA category	NO _x	SO _x	PM _{2.5}
Barge	C1 & C2 marine vessels	68.08%	7.95%	71.79%
Pipeline	Electricity-generating units	6.24%	79.34%	16.72%

⁶⁶¹ Office of Air and Radiation and Office of Air Quality, pp. 1 – 108 (2018).

⁶⁶² *Id.*; Wolfe *et al.* (2019).

⁶⁶³ Using reference baseline year 2025 in GREET. These values can be found in the ‘T&D Flowcharts’ tab of the GREET model.

⁶⁶⁴ Calculated using year 2025 in GREET.

Rail	Rail	0.81%	0.15%	0.47%
Truck	On-road heavy-duty diesel	24.87%	12.56%	11.02%

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. NHTSA completes these calculations for years 2025 and 2030. The sectors in the 2019 mobile sources paper only show health incidence per ton estimated for the year 2025, but NHTSA believes this information is the most up-to-date available, after communications with the study authors. The use of 2025 health incidence for all years implies a slight underestimation in 2030.

5.4.1.4. Health Incidence per Ton Values Associated with the Refineries Sector

NHTSA matches 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 5-9 shows the various types of health effects per ton corresponding to each pollutant emitted from the refineries sector. The health effects in the CAFE Model analysis correspond to the structure of the 2018 EPA source apportionment TSD, which focuses on the health effect endpoints shown in the table below.

Table 5-9: Health Incidences per Ton from the Refineries Sector

Health Effects	2025			2030		
	NO _x	SO _x	PM _{2.5}	NO _x	SO _x	PM _{2.5}
Premature Mortality - (Krewski)	0.00087	0.0088	0.041	0.00094	0.0095	0.044
Respiratory emergency room visits	0.00045	0.0047	0.023	0.00047	0.0049	0.024
Acute bronchitis	0.0013	0.013	0.061	0.0014	0.014	0.066
Lower respiratory symptoms	0.016	0.16	0.78	0.018	0.18	0.84
Upper respiratory symptoms	0.023	0.23	1.1	0.025	0.25	1.2
Minor Restricted Activity Days	0.67	6.8	32	0.68	7.0	33
Work loss days	0.11	1.2	5.4	0.12	1.2	5.6
Asthma exacerbation	0.027	0.28	1.3	0.029	0.29	1.4
Cardiovascular hospital admissions	0.00022	0.0023	0.010	0.00024	0.0026	0.012
Respiratory hospital admissions	0.00021	0.0022	0.010	0.00024	0.0025	0.011
Non-fatal heart attacks (Peters)	0.00088	0.0091	0.041	0.00097	0.010	0.045
Non-fatal heart attacks (All others)	0.000095	0.00099	0.0045	0.00010	0.0011	0.0049

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. While the Wolfe *et al.* paper does not report incidences per ton, EPA provided this information.

NHTSA matches three source categories from the Wolfe *et al.* paper to the CAFE Model LDV downstream emissions inventory: “on-road LD gas cars and motorcycles,” “on-road LD gas trucks,” and “on-road LD diesel.”⁶⁶⁵

Table 5-10: Health Incidences per Ton from On-Road Vehicles Sector⁶⁶⁶

Health Effects	On-Road LD Gas Cars and Motorcycles			On-Road LD Gas Trucks			On-Road LD Diesel		
	NO _x	SO _x	PM _{2.5}	NO _x	SO _x	PM _{2.5}	NO _x	SO _x	PM _{2.5}
Premature Mortality - (Krewski)	0.00075	0.013	0.073	0.00068	0.011	0.061	0.00060	0.031	0.050
Respiratory emergency room visits	0.00039	0.0076	0.041	0.00035	0.0061	0.035	0.00032	0.019	0.029
Acute bronchitis	0.0010	0.020	0.11	0.00096	0.016	0.091	0.00085	0.047	0.075
Lower respiratory symptoms	0.013	0.25	1.4	0.012	0.20	1.2	0.011	0.59	0.95
Upper respiratory symptoms	0.018	0.35	2.0	0.017	0.28	1.7	0.015	0.84	1.35
Minor Restricted Activity Days	0.53	11	60	0.49	8.5	49	0.44	25	40
Work loss days	0.090	1.8	10	0.084	1.4	8.4	0.075	4.3	6.9
Asthma exacerbation	0.022	0.42	2.3	0.020	0.33	1.9	0.018	1.0	1.6
Cardiovascular hospital admissions	0.00019	0.0036	0.020	0.00017	0.0028	0.016	0.00015	0.0085	0.013
Respiratory hospital admissions	0.00018	0.0034	0.018	0.00016	0.0027	0.015	0.00015	0.0081	0.013
Non-fatal heart attacks (Peters)	0.00075	0.014	0.076	0.00068	0.011	0.064	0.00060	0.033	0.053
Non-fatal heart attacks (All others)	0.000080	0.0015	0.0082	0.000073	0.0012	0.0069	0.000065	0.0035	0.0057

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, or economic valuation). NHTSA uses a BPT approach to estimate health impacts from changes in criteria pollutant emissions and the resulting monetized benefits, which are discussed further in Final TSD 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

⁶⁶⁵ Wolfe *et al.* (2019).

⁶⁶⁶ The only values estimated in this source are estimated for 2025 are carried forward to other analysis years.

quantified benefits. Some key assumptions associated with PM_{2.5}-related health benefits and uncertainties associated with the BPT approach are described below.

NHTSA assumes 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 concludes 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.”⁶⁶⁷

NHTSA assumes the health impact function for fine particles is log-linear without a threshold. 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.

NHTSA assumes a “cessation” lag between the change in PM exposures and the total realization of changes in mortality effects. Specifically, NHTSA assumes 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 Effects Subcommittee.⁶⁶⁸ This affects the valuation of mortality benefits at different discount rates. The above assumptions are subject to uncertainty.

NHTSA is more confident in the magnitude of the risks it estimates from simulated PM_{2.5} concentrations that coincide with the bulk of the observed PM concentrations in the epidemiological studies that are used to estimate the benefits. In contrast, NHTSA is less confident in the risk it estimates 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 the agency’s confidence in reported associations decreases appreciably. The scientific evidence provides no clear dividing line. Applying BPT values to estimates of changes in policy-related emissions precludes the agency 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 does 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.⁶⁶⁹

National-average BPT values reflect the geographic distribution of the underlying modeled emissions used in the calculation, which may not exactly match the geographic distribution of the emission reductions that 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 NHTSA assumes 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

⁶⁶⁷ EPA, Integrated Science Assessment (ISA) for Particulate Matter, EPA/600/R-19/188, EPA: Washington, D.C. (2019), available at: <https://www.regulations.gov/document/EPA-HQ-OAR-2014-0128-0049> (accessed: May 13, 2026).

⁶⁶⁸ See EPA, Advisory Council on Clean Air Compliance Analysis Response to Agency Request on Cessation Lag, EPA-COUNCIL-LTR-05-001, Docket ID NHTSA-2021-0053 (2004).

⁶⁶⁹ See EPA, Regulatory Impact Analysis for the Proposed Revisions to the National Ambient Air Quality Standards for Particulate Matter, Docket ID NHTSA-2017-0069-0344 (2012).

and photochemically modeled $PM_{2.5}$ concentrations are used to derive the BPT values but may not match the changes in air quality that would result from this final rule.

6. Simulating Economic Effects of Regulatory Alternatives

6.1. Costs and Benefits to Consumers

Many of the benefits and costs attributable to CAFE standards are private impacts that fall on buyers of new vehicles produced in the affected model years. These benefits and costs are primarily attributable to changes in vehicle ownership and operating costs that result from changes to vehicles manufacturers make to meet fuel economy standards, and to the costs of technology required to improve vehicles' fuel economy. Adding technologies that boost vehicles' fuel economy increases manufacturers' costs to produce them, and manufacturers pass those cost increases along to consumers in the form of higher purchase prices. Higher purchase prices for new vehicles also mean buyers face added expenses for sales taxes, registration fees, and insurance on their new vehicles. Initial buyers and subsequent owners of new vehicles experience reduced fuel costs over their vehicles' lifetimes and save time by refueling them less frequently.

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

The economic effects described below are discussed from the perspectives of both increasing and reducing existing standards. When CAFE standards are reduced (as is the case in this final rulemaking), these effects will have the same initial causes as from an increase in standards, but will have the opposite direction; most important, the application of additional fuel-saving technologies may no longer be necessary when standards are reduced relative to a reference baseline level, and any costs associated with meeting higher fuel economy standards in that baseline become cost savings when standards decrease. Other effects change direction as well. Absent technology application, drivers of new vehicles face higher costs of driving their vehicles, and travel less. Reducing travel offsets some of the additional fuel costs that drivers face under reduced standards and lowers the driver's chances of being involved in a traffic accident but also takes away the added benefits that drivers would receive from making those extra trips.

6.1.1. Additional Consumer Purchasing Costs

Raising fuel economy standards increases the price of new vehicles, as well as various other costs that increase in proportion to their selling prices. For example, sales taxes and some State registration fees are calculated as a percentage of the vehicle's purchase price, and higher prices also raise insurance premiums for new vehicles. Conversely, lowering fuel economy standards reduces vehicle prices, leading to additional savings for taxes, registration fees, and insurance premiums. NHTSA estimates each of these costs as a percentage of new vehicles' selling prices and includes them in its analysis of costs and benefits as viewed from the consumer perspective. When these effects result in transfers of money between consumers and private businesses, or between consumers and the government, they are not included in the agency's cost-benefit evaluation of changing CAFE standards.

6.1.1.1. Sales Taxes and Vehicle Registration Costs

Sales taxes and registration fees for new vehicles generally are considered transfer payments between consumers and government agencies and do not represent real economic costs, but they do represent additional costs to consumers that need to be accounted for when viewing the impacts of changing CAFE standards from the perspective of vehicle buyers and owners. NHTSA uses a population-weighted average of State sales tax rates on purchases of new vehicles, which produces a nationwide average rate of 5.65 percent, to estimate sales taxes paid on purchases of new cars and light trucks.⁶⁷⁰

6.1.1.2. Insurance Costs

Expensive vehicles require more costly collision and comprehensive insurance to protect their owners against damages, theft, and other threats to their value.⁶⁷¹ NHTSA assumes that vehicles have the same exposure to the risk of crashes throughout their lifetimes when it calculates expected premiums and also accounts for depreciation in vehicles' value as they age and accumulate use, so the dollar amount their owners pay in value-related insurance declines as vehicles depreciate with age. 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 to consumers associated with higher payouts in the event the vehicle is totaled.⁶⁷²

Equation 6-1: Estimating Insurance Costs

$$(\text{Comprehensive \& Collision})_{\text{age}} = \frac{\text{MSRP} * (\text{share MSRP})}{(1 + \text{depreciation})^{\text{age}}} * (1 - 0.20)$$

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 necessary. Wards Automotive provides data on the average annual premiums paid for collision, comprehensive, damage, and liability insurance for new light trucks and passenger cars produced during MYs 1992-2003 but reports only the total amount of insurance premiums for MY 2004 and later. NHTSA calculated the share of total insurance premiums paid for collision and comprehensive insurance coverage over the lifetimes of MY 1979-2003 vehicles and found that it ranged from 49 to 55 percent, with the share tending to be largest towards the end of the time series. For trucks, this share ranged from 43 to 61 percent of total insurance premiums, again rising for more recent model years.

NHTSA assumes that for MYs 2004-2016, 60 percent of light truck insurance premiums and 55 percent of premiums for cars represents collision and comprehensive coverage and uses these assumed shares to compute the aggregate amount buyers of those vehicles paid for collision and comprehensive insurance

⁶⁷⁰ See Car Tax by State available at: <https://www.factorywarrantylist.com/car-tax-by-state.html> (accessed: May 22, 2026). 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. See new car sales by state available at: <https://www.factorywarrantylist.com/car-sales-by-state.html> (accessed: May 22, 2026).

⁶⁷¹ The agency assumes that insurance premiums are “actuarially fair,” meaning that they are set to equal the amount an insurance company pays in the event of an incident and claim, weighted by the risk of its occurrence.

⁶⁷² Industry reports indicate that between 2019 and 2022, the percent of car insurance claims for totaled or stolen vehicles increased from 19.1 percent to 27 percent, see Thompson, M. LexisNexis report: Total loss claims, damage severity rose in 2022, last revised: May 16, 2023, available at: <https://www.repairedrivenews.com/2023/05/16/lexisnexis-report-total-loss-claims-damage-severity-rose-in-2022/> (accessed: May 22, 2026).

coverage. It then weights these estimates by the shares of cars and light trucks making up each model year’s initial sales to estimate the average amount their buyers paid for collision and comprehensive insurance, as shown in Table 6-1. As the table shows, the annual collision and comprehensive insurance costs ranged from 1.74 to 2.03 percent of MSRP over MYs 2010-2016, averaging 1.83 percent of their initial MSRP. This is used as the share of the value of future new vehicles their buyers will pay for collision and comprehensive insurance, 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 of 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%
2010	\$548	\$29,076	1.88%

NHTSA uses recent data from Black Book and Fitch,⁶⁷³ which show annual depreciation rates of two- to six-year-old vehicles ranged from a high of 17.3 percent to a low of 8.3 percent prior to the Coronavirus disease of 2019 (COVID-19) pandemic. In 2020, depreciation rates dropped to about 2 percent and used car values actually increased during 2021 as constraints on the supply of new cars and light trucks raised demand for used vehicles. Since 2022, depreciation rates have returned to levels slightly above their average for the years before 2020-2021. Because rates observed during a period of abnormal supply constraints are unlikely to be representative of future model years’ depreciation profiles, NHTSA averages annual rates from 2016-2023 excluding 2020-2021 to construct a more representative depreciation rate (14.6 percent) to apply to future model years.⁶⁷⁴

When fuel economy standards are reduced and new vehicle prices decrease, the resulting lower insurance premiums reflect the reduced payouts insurers expect when less expensive vehicles suffer damage. This reduction in premiums represents a savings for vehicle owners that is attributable to resetting CAFE standards.

NHTSA multiplies total insurance costs by the percentage of insurance claims for vehicle repairs and treats the remainder as claims paid to owners of totaled and stolen vehicles. This approach yields a conservative estimate because the cost to replace a vehicle is typically higher than the cost to repair it, so the share of insurance outlays that cover replacements is likely to be higher than the fraction of claims for totaled or stolen vehicles. NHTSA estimates the percentage of claims for replacing totaled or stolen vehicles at 20 percent of insurers’ total outlays.⁶⁷⁵

⁶⁷³ See Black Book, Black Book-Fitch Ratings – Vehicle Depreciation Report 2024 (2024), available at: <https://www.blackbook.com/depreciation-reports/black-book-fitch-ratings-vehicle-depreciation-report-2024/> (accessed: May 22, 2026).

⁶⁷⁴ Including preliminary projections for 2024 and 2026 would bring the average depreciation rate to 15.6 percent. Given that these are projections for 2–6 year old vehicles, the agency has chosen to continue using the average value of 14.6 percent.

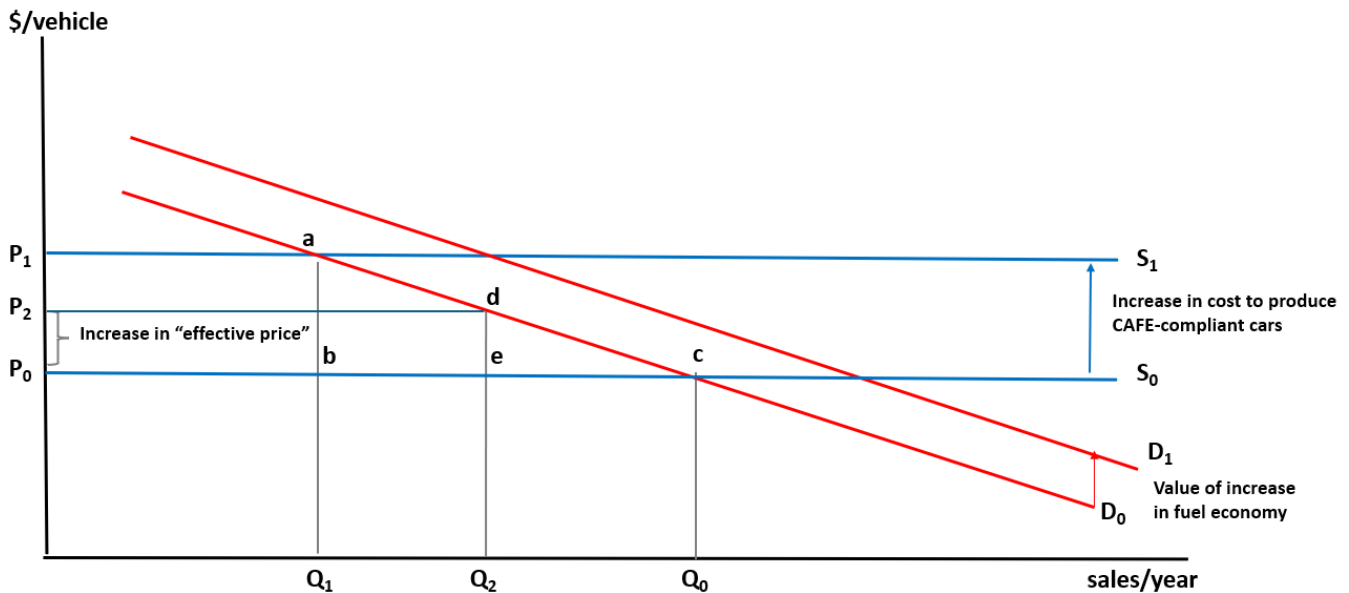
⁶⁷⁵ Krumlauf, K., & Bahnsen, E., CCC Intelligent Solutions: The Forces Shaping the U.S. Car Parc in 2025 and Beyond, last revised: 2025, available at: <https://www.cccis.com/reports/crash-course-2025/q1> (accessed: May 22, 2026).

6.1.2. Consumer Surplus from New Vehicle Sales

When government regulation causes the prices of goods to increase, consumers may choose to remain in the market and purchase those goods at an increased cost, or they may exit the market. In the latter case, would-be buyers who are deterred by higher prices experience a loss in welfare. When the agency increases CAFE standards, which leads to higher prices, some subset of buyers will refrain from purchasing new vehicles. The welfare loss to this subset of buyers is measured by the forgone consumer surplus they would have received from their purchase of a new vehicle in the absence of standards. Conversely, when CAFE standards are reduced, resulting in lower vehicle prices, some consumers are likely to enter the new vehicle market, which increases consumer welfare.

Figure 6-1 illustrates the loss in consumer surplus that results from raising CAFE standards;⁶⁷⁶ as indicated previously, the lower CAFE standards this final rule establishes will have exactly the opposite effect. In the figure, the supply curve S_0 and the resulting price P_0 reflect manufacturers' costs to produce vehicles meeting the previous CAFE standard. Raising standards increases the cost of producing CAFE-compliant vehicles, shifts the supply curve from S_0 to S_1 , increases vehicle selling price from P_0 to P_1 , and reduces the number of vehicles sold to Q_1 if their fuel economy remained unchanged.

Figure 6-1: New Vehicle Consumer Surplus



At the same time, however, complying with the higher standard requires producers of new cars and light trucks to increase their average fuel economy (though not necessarily the fuel economy of every model). As indicated previously, NHTSA assumes that after accounting for any sacrifices in other features, consumers value 36 months of fuel savings that vehicles featuring higher mpg offer, and the value of these savings is reflected by an upward shift of the demand curve in Figure 6-1 from D_0 to D_1 . The intersection of D_1 and S_1 determines the new equilibrium sales quantity Q_2 . The intersection of D_0 and Q_2 at point d illustrates the fact that the “effective price” increase, or the price change net of the improvement

⁶⁷⁶ 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 the 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 – 38.

in the quality of new vehicles, is only the distance from P_0 to P_2 rather than the full distance from P_0 to P_1 . Thus, the increase in demand offsets part of the price increase and limits the decline in the number sold to Q_2 rather than Q_1 .

The triangle formed by “d-e-c” in Figure 6-1 reflects the net loss in consumer surplus to would-be buyers of new cars and light trucks who viewed the previous combination of lower fuel economy and lower prices as preferable to increased fuel economy accompanied by higher prices, and thus elect not to purchase new vehicles. As the figure shows, it is smaller than the loss in consumer surplus that would have resulted from higher prices without the accompanying increase in fuel economy, which would have reduced sales to Q_1 and resulted in a loss in consumer surplus equal to the triangle “a-b-c.”

Under this reset of the CAFE standards, consumer surplus will increase compared to the baseline because manufacturers’ savings in regulatory costs will be passed on to new car and light truck buyers in the form of lower prices or product enhancements to entice customers, given the intensely competitive nature of the automotive industry. Consumers who would have been deterred by higher prices under the 2022 and 2024 standards will again elect to purchase new vehicles, and restoring the availability of models offering lower fuel economy at reduced prices will improve consumer welfare (*i.e.*, they will gain consumer surplus).

6.1.3. Implicit Opportunity Cost

The agency’s regulatory analysis of CAFE standards initially focuses on their likely impact on the fuel economy levels new vehicles achieve and the accompanying changes in their selling prices. In establishing standards, however, the agency must also consider that new vehicles’ potential buyers and users value a wide range of other features those vehicles offer. These attributes include occupant protection and other safety features, vehicle size and carrying capacity (for both passengers and luggage or cargo), ride comfort, and performance features such as acceleration, braking, and maneuverability. Many of the technology investments that manufacturers make to improve vehicle efficiency in converting stored fuel energy to mechanical propulsion could instead be directed toward improving some or all these other attributes. In other cases, improving a vehicle’s other features may not directly affect its fuel efficiency but manufacturers looking to preserve a vehicle’s cost and prevent a decline in sales may have to choose between adding the feature or adding fuel saving. In both examples, manufacturers face trade-offs when considering which features to improve.

During periods when CAFE standards have remained unchanged over successive model years, manufacturers have offered improvements in these other attributes on many of their models (as well as some voluntary increases in many models’ fuel economy), demonstrating that they believe buyers value these other features sufficiently to justify the higher costs and selling prices for offering them. As shown in Table 6-2, during the period when CAFE standards did not increase for either passenger cars or light trucks (1985-2005), fuel economy on average remained essentially unchanged, while acceleration improved at about a quarter of a second per year.

Over a timeframe of similar length (2005-2024) during which fuel economy standards increased significantly, manufacturers invested in improving fuel economy, resulting in an average increase of just under 0.4 mpg per year. This created value for consumers in the form of shaving about one-fifth of a cent off of fuel costs per mile (at \$3-per-gallon gasoline prices). However, over this same timeframe, improvements in acceleration have slowed markedly, to about one-third of the rate of improvement during the prior period. While acceleration, like other attributes, faces diminishing returns to improvements, even narrowing the time window to 2000-2010 shows that acceleration improved about three times faster in the five years before 2005 compared to the five years after.

Table 6-2: Historical Fleetwide Improvements in Fuel Economy and Acceleration⁶⁷⁷

	Average Increase in Fuel Economy (mpg)	Average Decrease in Fuel Cost per Mile at \$3 per gallon (cents)	Average Decrease in 0-60 mph Acceleration, seconds
1985-2005	-0.07 (-0.3% per year)	-0.05	0.25 (2.2% per year)
2005-2024	0.38 (1.6% per year)	0.21	0.08 (1.0% per year)

One reason manufacturers may have preferred to improve acceleration rather than fuel economy when fuel economy regulations remained flat is the high value consumers place on performance attributes. Table 6-3 reproduces estimates from a meta-analysis of estimates taken from the economics literature in Greene *et al.* (2018). The authors show average consumer valuations on either a 1-cent improvement in fuel costs per mile or a 1 second reduction in 0-60 mph acceleration. While estimates vary based on the methodology used, they show that consumers value these two improvements about equally on average. Estimates from the literature also indicate that improvements to acceleration of this magnitude tend to be less costly than fuel economy improvements.⁶⁷⁸ Together, the relative values that consumers appear to place on fuel savings and performance, and the relative costs required to improve each, help to explain why manufacturers tended to invest more in performance than fuel economy in the absence of binding standards.

Table 6-3: Estimates of Consumer Willingness to Pay for Fuel Savings and Acceleration (\$2015)⁶⁷⁹

Data Type	\$0.01/mile Improvement in Fuel Savings	1 second Reduction in 0-60 mph Acceleration
Market Sales	\$678	\$685
Revealed Preference Survey	\$549	\$847
Stated Preference Survey	\$1,225	\$979
Market + Revealed Preference	\$693	\$796
All	\$853	\$845

For the final rule, the agency is correcting the market distorting effects of previously established CAFE standards, which would have required manufacturers to channel technology toward improving fuel economy while deferring or forgoing planned improvements in their models’ other desired features to keep prices at levels that preserve vehicle sales. These standards may have led manufacturers to postpone—or in extreme cases, cancel—improvements in those features they would otherwise have made.

Forcing manufacturers to make these trade-offs reduces new vehicles’ perceived value to their potential buyers and thus imposes an additional cost of meeting CAFE standards, regardless of whether a consumer ultimately elects to purchase a new vehicle. This can lead consumers to retain their used vehicles longer or replace them with newer—but still used—models and to forgo purchasing new, safer vehicles. The following sections explain the nature of this “opportunity cost” in more detail, discuss how the agency has

⁶⁷⁷ See EPA Automotive Trends Report, 2026, Table A-1., available at: <https://www.epa.gov/automotive-trends/explore-automotive-trends-data#SummaryData> (accessed: May 14, 2026).

⁶⁷⁸ For example, Knittel (2011) and Klier and Linn (2016) estimate a trade-off of between 3–6 percent improvement in horsepower (which is a determinant of acceleration) for every 1 percent improvement in fuel economy. Watten and Anderson (2025) find an average rate of around 1.4 percent improvement in horsepower to weight for every 1 percent improvement in fuel economy, though the rate varies over time and is closer to 2 percent in recent years.

⁶⁷⁹ Estimates taken from Greene, D. *et al.*, Consumer Willingness to Pay for Vehicle Attributes: What Do We Know? Transportation Research Part A: Policy and Practice vol: 118(c): pp. 258–279 (2018).

treated it in past regulatory analyses, and describe how NHTSA attempts to measure it for the current final rule.

The final rule lowers the stringency of current CAFE standards, enabling manufacturers to resume or accelerate planned improvements in features other than fuel economy. This will increase their models' appeal to potential buyers, make them more competitive in the new car marketplace, and by doing so, lower the opportunity cost of meeting the CAFE standards.

6.1.3.1. Imposing a New CAFE Standard

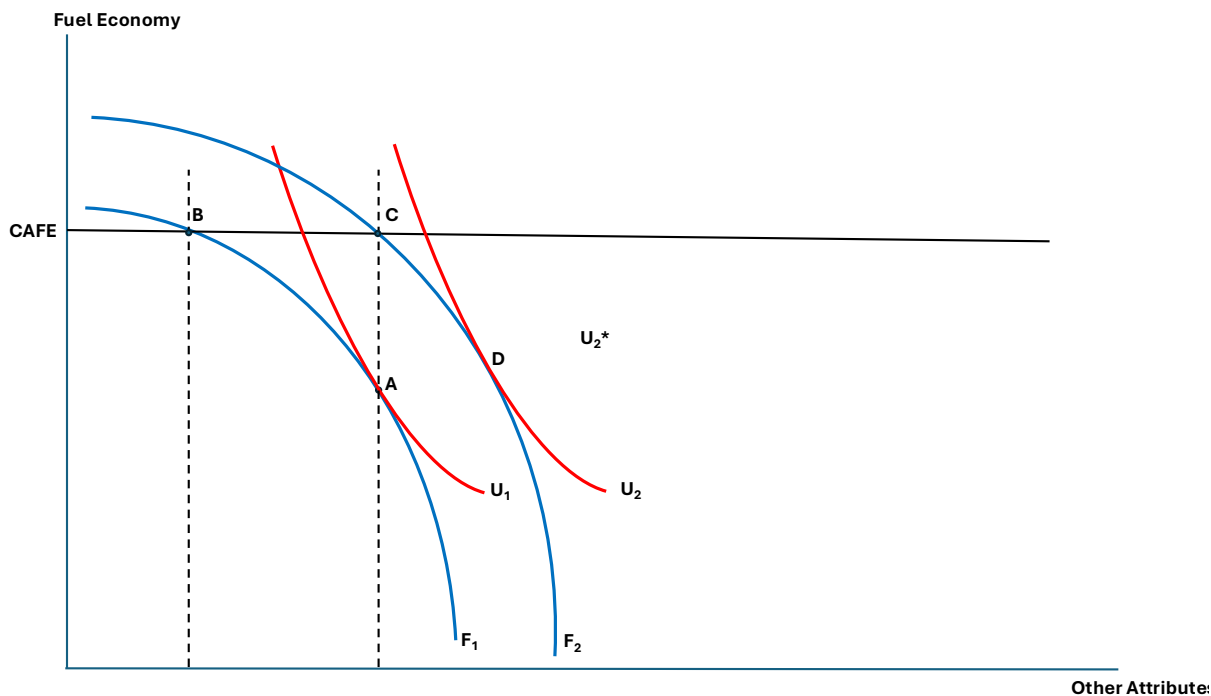
Figure 6-2 shows the effect of imposing CAFE standards when fuel economy was previously unregulated. The concave shapes (shown in blue) represent alternative combinations of fuel economy and an alternative attribute that a manufacturer could offer on a new vehicle model equipped with a given level of technology and production cost.⁶⁸⁰ As the shapes of these “production frontiers” indicate, higher levels of fuel economy can be achieved by sacrificing improvements in that other attribute, but the rate at which the two features can be traded off varies along each frontier.

By equipping a vehicle with additional technology, manufacturers can shift the frontier outward, offering both higher fuel economy and more of the competing attribute, but this adds costs that must be recovered by raising the vehicle's selling price. The downward sloping red shapes illustrate combinations of fuel economy and the alternative attribute that potential buyers find equally attractive; these reveal trade-offs between the two as viewed from the perspective of consumers, who require progressively larger improvements in either attribute to compensate for further sacrifices in the other.⁶⁸¹

⁶⁸⁰ These convex shapes are two-dimensional slices through a multi-dimensional surface showing combinations of fuel economy and various other features of vehicles that the same complement of technologies could be used to provide. In cases in which attributes do not directly affect the fuel efficiency of the vehicle, these can be thought of as isocost curves representing combinations of fuel-saving technology and other features that require the same level of production cost.

⁶⁸¹ Again, these are two-dimensional slices through a multi-dimensional surface showing combinations of various attributes that potential buyers find equally appealing.

Figure 6-2: Opportunity Cost of Imposing a New CAFE Standard



In an unregulated market, a manufacturer would respond to buyers' valuation of fuel economy and the competing attribute by equipping its vehicle model with a level of technology that enables it to provide combinations of the two features along the frontier labeled F_1 . Offering the combination of fuel economy and another feature shown by point A would maximize the model's appeal to potential buyers and thus its sale value.

Imposing a new CAFE standard requiring the minimum level of fuel economy shown in the figure presents a manufacturer with a range of choices. At one extreme, a manufacturer could sacrifice the model's other attribute and move along frontier F_1 to reach the required level of fuel economy with no increase in its production cost, thus offering the combination of fuel economy and the other attribute at point B to potential buyers without raising its price. At the other extreme, a manufacturer could install sufficient additional technology—at a potentially significant cost—to reach point C on frontier F_2 , enabling that same model to meet the new CAFE standard without sacrificing the model's other attribute.

Many intermediate compliance strategies are possible, and each would involve a combination of direct monetary costs to shift the frontier to a location between F_1 and F_2 and movements along the resulting frontier (*i.e.*, sacrifices in the other attribute) sufficient to meet the CAFE standard. Each strategy involves some combination of higher costs (and selling price) and sacrifices in the vehicle's other attribute. NHTSA presumes that manufacturers will choose the profit-maximizing marketing strategy, and the resulting combination of fuel economy will reflect the costs of adding technology as well as buyers' valuation of improved fuel economy and the competing attribute.

While moving to frontier F_2 enables a manufacturer to meet the CAFE standard without compromising the model's other current features, in an unregulated market it could also have offered the combination of features shown by point D, making its model still more valuable to buyers, but only at an increased cost. Thus, the opportunity cost of the compliance strategy illustrated by the move from point A to point C is the sacrifice in the vehicle's market value indicated by the difference between the convex shapes U_1 and

U₂. Intermediate strategies between points B and C would each entail different combinations of increased production cost (and thus selling price) and the opportunity cost to buyers from the sacrifice in this model's non-fuel economy attribute. In each case, the opportunity cost is generated by the effect of the standard on the manufacturer's choice set, since imposing a minimum standard renders some combinations of fuel economy and other attributes infeasible.

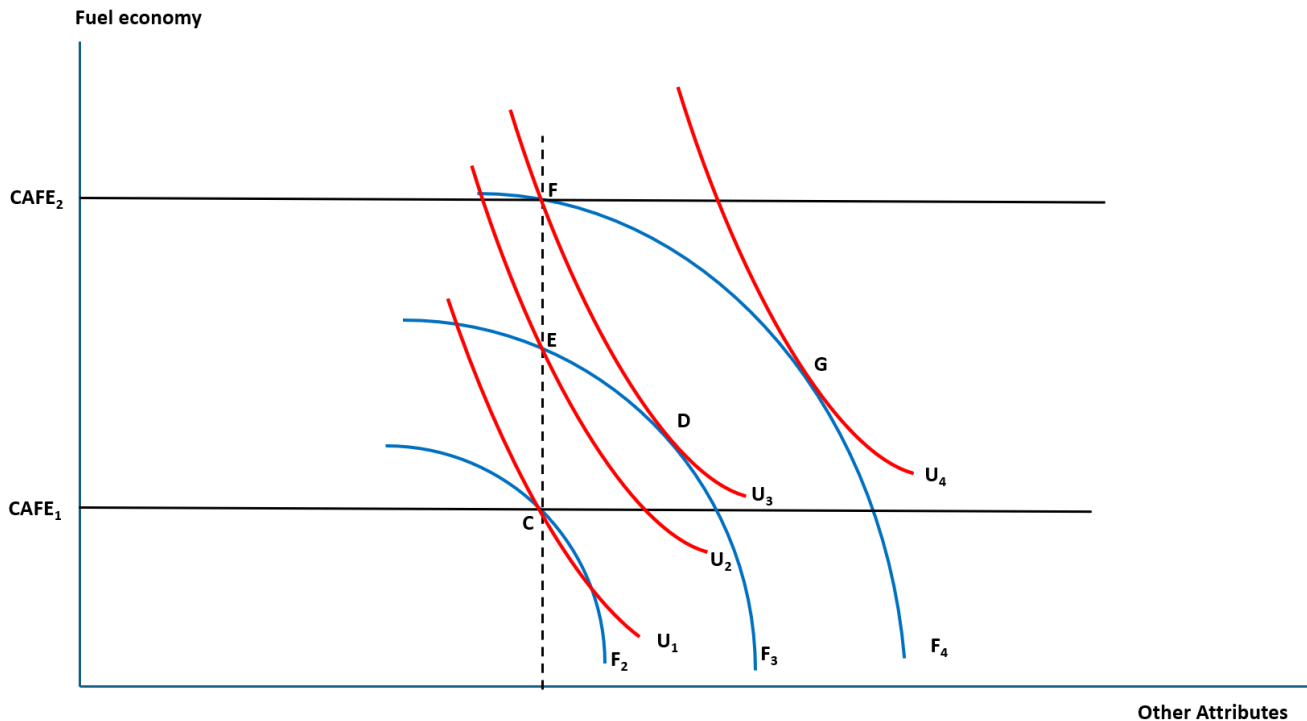
NHTSA's CAFE Model and regulatory analysis assume that manufacturers will not sacrifice any of their models' other desirable features to meet CAFE standards, in effect assuming point C always represents their chosen compliance strategy. NHTSA assumes that the direct monetary outlay required to shift the frontier outward from F₁ to F₂ is ultimately borne by consumers, via the associated increase in its selling price and the loss in consumer surplus from the resulting decline in its sales (as described in Chapter 6.1.2 above). The CAFE Model's estimate of benefits consists mainly of the reduction in fuel use, plus ancillary benefits such as the increased convenience from less frequent refueling.

6.1.3.2. Changing an Existing CAFE Standard

Measuring the change in the opportunity cost of manufacturers' strategies for complying with fuel economy standards is somewhat more complicated when a standard already in place is being changed. In the previous Figure 6-2, a manufacturer subject to an initial standard (CAFE) could comply by offering the combination of fuel economy and another attribute shown by point C. If meeting the CAFE standard required manufacturers to exhaust all technology available to them at reasonable costs, increasing fuel economy further *and* improving the competing feature to reach point G would require significant cost (and price) increases. In that case, most manufacturers would simply decide to do neither, resulting in exact compliance with the standard at point C.

With a reduction of CAFE standards, shown in Figure 6-3 as moving from CAFE₂ to CAFE₁, manufacturers can choose to offer combinations of fuel economy and other features that are more attractive to buyers than those required to meet the stricter standard. In the graph below, this is represented by manufacturers offering the combination of attributes at point G rather than point F. Improving the competing attribute more than offsets the sacrifice in fuel economy, since G lies on the curve U₄, meaning that buyers prefer the attribute combinations it represents to those along U₃. There is no resulting increase in cost, since points F and G lie on the same blue curve, indicating that they use the same technology. This reduced opportunity cost of complying with standards is a result of expanding the choice set of desirable vehicle features for consumers.

Figure 6-3: Opportunity Cost of Changing an Existing CAFE Standard



Conversely, raising the standard from $CAFE_1$ to $CAFE_2$ will leave the vehicle’s manufacturer with little choice except to incur the cost of installing additional technology necessary to move the frontier outward from F_2 to F_4 , and to deploy those technologies exclusively to increase fuel economy, meeting the higher standard at point F . This generates additional fuel savings with a value represented by the distance between U_1 and U_3 , requiring a technology cost represented by moving from F_2 to F_4 , and imposing an opportunity cost represented by the difference between U_4 and U_3 . Even though there is no horizontal difference between points C and F —indicating that they offer the same level of the competing attribute—manufacturers are likely to prefer using additional technology to reach frontier F_4 —improving both fuel economy and other attributes to reach point G —but the need to meet the higher CAFE standard would effectively force them to use the additional technology exclusively to improve fuel economy.

If the standard remained at $CAFE_1$ and additional or more effective technology became available at reasonable cost—either because of learning and volume effects reducing its original manufacturing costs, or the introduction of entirely new technology—the vehicle’s manufacturer would presumably take advantage of the reduction in cost by improving its other attributes to make it more appealing to buyers. In the process, a manufacturer might also employ some of the energy efficiency benefits offered by the added or improved technology to increase the model’s fuel economy beyond the level required to comply with $CAFE_1$. In this example, the manufacturer would voluntarily incur the cost required to shift the frontier from F_2 to F_3 , offering the combination of attributes shown by point D , and $CAFE_1$ would no longer be a binding standard.

Raising the standard to $CAFE_2$ would preempt this strategy by requiring a manufacturer to incur the cost of shifting the frontier outward to F_4 to provide the combination of fuel economy required to meet the higher standard and the competing attribute shown by point F . Since the relevant no-action counterfactual is now point D instead of point C , the analysis supporting this final rule uses a baseline represented by D ; the relevant technology cost of raising the standard is now that required to shift the frontier outward from F_3 to F_4 and enable the manufacturer to meet $CAFE_2$ while the resulting fuel savings are captured by the

vertical difference between D and F. Nevertheless, the reduction in opportunity cost from setting the standard at $CAFE_1$ instead of $CAFE_2$ is still the difference between U_4 and U_3 , since with the standard remaining at $CAFE_1$ the manufacturer could offer the combination of features shown by point G at the same cost it would incur to meet $CAFE_2$. Points D and F both lie on U_3 , indicating that the change in standards provides no additional private benefits to the consumer, as the loss in the value of its other features exactly offsets the additional value of fuel savings.

However, the exact case shown may be unlikely. In the more general situation where a manufacturer voluntarily increases fuel economy beyond what $CAFE_1$ requires while also improving the competing attribute, the value of requiring a further increase in fuel economy to $CAFE_2$ would not be exactly offset by the opportunity cost of the required sacrifice in a competing feature. Still, the resulting opportunity cost would add to the incremental technology outlay required to comply with the more demanding standard, and their sum should be compared to the value of fuel savings from the required increase in fuel economy to measure the policy’s net benefits to vehicle buyers.⁶⁸²

6.1.3.3. What Does NHTSA’s CAFE Model Measure?

NHTSA’s CAFE Model makes certain simplifying assumptions in the interest of simulating real-world responses by vehicle manufacturers and buyers while maintaining tractability. As indicated previously, one assumption is that manufacturers will not compromise or improve the passenger- and cargo-carrying capacity, comfort, performance, or safety features of their existing models as part of their efforts to meet fuel economy regulations. An important limitation of the CAFE Model is that it does not simulate the potential effects of technologies that improve the energy efficiency of vehicle’s engines or drivetrains on features other than fuel economy—acceleration or passenger comfort, for example—and instead assumes that the efficiency benefits of all technology added to existing models will be channeled exclusively into improving their fuel economy. These simplifying assumptions combine to make the CAFE Model unsuitable for some purposes, including directly measuring the opportunity cost of meeting fuel economy standards. In the following section, NHTSA explains how it develops an approximation of the opportunity cost in establishing standards.

Referring again to Figure 6-3, if a manufacturer decides to improve a model’s features—incidentally including its fuel economy—beyond the level required to meet prevailing demand, the CAFE Model cannot identify the resulting combinations of attributes represented by points such as D or G. This is because it is unable to “partition” the benefits of vehicle technologies between improving fuel economy and other features and instead assumes all efficiency improvements are deployed solely to increase fuel economy. In the case where a manufacturer voluntarily adds technology to shift its attribute frontier from F_2 to F_3 , the CAFE Model can identify point E but is unable to pinpoint other attribute combinations along F_3 , including the value-maximizing combination of improvements shown by point D. This means the CAFE Model is likely to underestimate the level of market-driven technology adoption that is *not* a response to higher standards.

Similarly, the CAFE Model cannot locate the value-maximizing combination of attributes along frontier F_4 represented by point G, and instead can only simulate the combination shown by F. This limitation means that the Model cannot directly measure the sacrifice in a vehicle model’s utility or value to potential buyers that results from requiring its manufacturer to meet the more demanding standard $CAFE_2$, rather than allowing it to offer more desirable combinations of fuel economy and other features at the same cost.

⁶⁸² The policy also would have minor ancillary benefits such as the value of less frequent refueling, and costs such as the loss in consumer surplus from reduced sales.

6.1.3.4. Approximating the Opportunity Cost

Because of this limitation, NHTSA must estimate the opportunity cost of improvements in vehicles' other features that are precluded when complying with progressively higher CAFE standards requires their manufacturers to focus exclusively on improving their fuel economy. NHTSA approximates that cost by assuming it must be large enough to account for buyers' apparent unwillingness to purchase models offering higher fuel economy even when the resulting savings in their future fuel costs would repay their higher purchase price. NHTSA reviewed recent research on car buyers' WTP for higher fuel economy in Chapter 4.2.1.1 and concludes that absent any accompanying sacrifice in other features, consumers value about 75 percent of the appropriately discounted future fuel savings from purchasing a more fuel-efficient model, which the typical buyer would realize over the first 10 years of its expected lifetime.⁶⁸³

As discussed in Final TSD Chapter 4.2.1.1, NHTSA analyzed modeling assumptions for the payback period and found that a period of 36 months produced results that were most consistent with technology adoption in the observed fleet, while extending the payback period to 60 months worsened the model's accuracy. This reveals a gap between how much consumers appear to value fuel savings in the absence of any trade-off and how much manufacturers anticipate they will be willing to pay when these improvements are bundled with any trade-offs that come with making fuel efficiency improvements to a new vehicle. Given the apparent preference of consumers for attributes like acceleration, and manufacturers' preference for improving these features more rapidly during periods of non-rising CAFE standards, NHTSA believes that a plausible explanation for this difference is that adopting more demanding CAFE standards forces manufacturers to postpone or forgo planned improvements to vehicles' other attributes as part of their efforts to comply, and sacrificing those improvements offsets part of the value of those fuel savings. Thus, on balance, buyers appear willing to pay only for improvements in fuel economy whose undiscounted fuel savings repay the higher purchase prices of models offering them within three years, and NHTSA terms this shorter time horizon the payback period.

To make this approximation, NHTSA calculates the savings in discounted fuel costs a higher mpg model would provide beginning in its fourth year and extending through its tenth year of use, using fuel prices prevailing during the year in which the new vehicle is sold. Again, the logic underlying this approach is that recent research (reviewed in detail in Chapter 4) suggests that car buyers value between 50 percent and 100 percent of discounted lifetime fuel savings for new vehicles. NHTSA assumes that on average buyers value approximately 75 percent (the mid-point of that range) of the savings in future fuel costs they expect from purchasing a higher mpg model, and new cars are typically driven that same fraction of their expected lifetime mileage over the first 10 years after they are initially purchased.

The agency's view is that the most likely explanation for buyers' behavior is that the value of improvements in vehicles' other features that manufacturers forgo to meet more stringent CAFE standards must be large enough to offset the savings in fuel costs that higher mpg models would provide to their original buyer, plus a portion of the savings they are expected to provide to any subsequent owners. While the original owner will not directly benefit from fuel savings achieved after selling a vehicle, some fraction of this additional value is likely to be capitalized into its resale value. Under NHTSA's approach, this implicit opportunity cost (IOC) offsets about half of the expected discounted fuel savings remaining

⁶⁸³ Estimates from the literature of consumer willingness to pay for the value of any fuel savings generated by purchasing a new vehicle show a wide range of valuation shares. As discussed in Final TSD Chapter 4.2.1.1 the methodology used to estimate the valuation share appears to play an important role because stated preference studies tend to find higher valuation shares than revealed preference and market sales studies. Full valuation exists within the range of estimates, but at the upper end. NHTSA uses 75 percent as a conservative choice at the middle of the range of estimates found in the literature. This leaves about 25 percent of lifetime fuel savings that are modeled as not being valued by consumers and not offset by the IOC. Possible explanations for this include differences in private discounting between consumers and the authors, and the inability of consumers to capture the full residual value of their vehicle on the used market.

after the first owner’s average length of ownership. Overall, for cars, the IOC offsets slightly more than 40 percent of discounted lifetime fuel savings from purchasing a more fuel-efficient model.

Thus, rather than assuming buyers will simply ignore a substantial fraction of the lifetime fuel savings that models with higher fuel economy offer—as it has done in past regulatory analyses—NHTSA now assumes that buyers (and subsequent owners) of new cars and light trucks value 75 percent of the savings in fuel costs they expect from purchasing a higher mpg model, which is equivalent to the fuel-cost savings these vehicles produce over the first 10 years of their lifetimes. At the same time, the agency also assumes that the opportunity cost of improvements in a vehicle’s other features that manufacturers would defer or forgo to enable them to comply with stricter CAFE standards is large enough to offset a substantial fraction of that value, in effect shortening the period over which they demand that higher fuel economy “pay for itself” from 10 to 3 years.

Exactly the opposite reasoning applies when the stringency of CAFE standards is reduced: by enabling manufacturers to offer combinations of fuel economy and other features that are more attractive to buyers than those required to meet a stricter standard, reducing the stringency of prevailing CAFE standards reduces the opportunity cost of complying. By doing so, it provides important benefits to buyers by expanding their range of choice among competing models’ features, rather than limiting consumers’ choices to combinations of features that include higher fuel economy than they would voluntarily purchase.

6.1.4. Value of Fuel Spending

Changes to CAFE standards alter the amount that drivers spend on fuel. When standards force additional technology to be adopted, this results in a fuel savings benefit for drivers. When standards are reduced and this technology is not adopted, fuel spending increases. The economic value of any fuel spending is calculated by multiplying the change in fuel consumption that results from sales and use of vehicles whose fuel economy is affected by changes in the standards by fuel prices projected over those vehicles’ lifetimes. Under each regulatory alternative, all vehicle models of a given body style and age are assumed to be driven the same distance at each age, and drivers nationwide are assumed to face identical fuel prices in each future calendar year. Dividing a vehicle’s annual mileage by its average fuel economy yields an estimate of its average yearly fuel consumption, and the differences between its fuel consumption under the baseline and each regulatory alternative represent the change in the number of gallons (or quantity of fuel energy) its buyer would purchase with each alternative CAFE standard in effect.

Under these assumptions, NHTSA’s estimates of fuel spending from changing the fuel economy of an individual model depend only on how much its fuel economy is affected, and do not reflect whether its actual use differs from other models of the same body type (after accounting for the fuel economy rebound effect on driving). Neither do NHTSA’s estimates of fuel consumption account for variation in how much individual vehicles of the same body type and age are driven at each age, which appears to be significant (see Chapter 4.3.1).

Consumers spending on fuel is valued at the average retail fuel price projected for each future calendar year, which includes both the Federal fuels tax and an average of State fuel taxes (fuel price assumptions are discussed in detail in Chapter 4.1.2). Fuel taxes represent transfers from drivers to government agencies and thus have no net effect on the benefit-cost analysis, but consumers value fuel expenditures at retail fuel prices (which include taxes) so it is important to account for the offsetting change in tax revenue to government agencies.

Assuming each vehicle is driven the same number of miles as others of the same body style and age each year may underestimate fuel consumption under more stringent standards. Because the distribution of annual miles driven 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 higher standards, even when the fuel economy values of different models are correctly averaged.⁶⁸⁴ This will be the case even when increases in fuel economy can be estimated reliably for individual models, 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 its fuel economy under alternative standards.

For example, NHTSA estimates that new automobiles are driven an average of 17,000 miles during their first year.⁶⁸⁵ 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 30 and 40 mpg, they will consume a total of 967 gallons annually.⁶⁸⁶ Improving the fuel economy of each model by 5 mpg will reduce their total fuel use to 844 gallons, thus saving 122 gallons annually.⁶⁸⁷ In contrast, using the 17,000-mile average figure for both vehicles yields estimated fuel savings of 128 gallons per year from that same 5-mpg improvement, about 5 percent above the correct value.⁶⁸⁸

The magnitude of this potential overestimate of fuel savings increases with the strength of 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 they drive directly affects their fuel costs and thus the savings they obtain from driving a model that features higher fuel economy.⁶⁸⁹ Such behavior—whereby 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 based on empirical estimates of average vehicle use. Thus, to the extent it occurs, NHTSA is likely to overstate actual fuel savings from raising fuel economy standards. NHTSA is also likely to 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 agency's analysis to overstate the difference in the *value* of fuel spending resulting from changing standards as well. As with miles driven, NHTSA's analysis assumes all vehicle owners pay the national average fuel price at any time. However, fuel prices vary substantially across 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,

⁶⁸⁴ 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 MPG₁ and MPG₂ that are driven identical amounts, their harmonic average fuel economy is equal to $2/(1/MPG_1 + 1/MPG_2)$.

⁶⁸⁵ 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.

⁶⁸⁶ Calculated as $(14,000 \text{ miles}/30 \text{ miles per gallon}) + (20,000 \text{ miles}/40 \text{ miles per gallon}) = 966.66 \text{ gallons}$.

⁶⁸⁷ Calculated as $(14,000 \text{ miles}/35 \text{ miles per gallon}) + (20,000 \text{ miles}/45 \text{ miles per gallon}) = 844.44 \text{ gallons}$.

⁶⁸⁸ NHTSA's estimate of their combined initial fuel consumption would be $(17,000 \text{ miles}/30 \text{ miles per gallon}) + (17,000 \text{ miles}/40 \text{ miles per gallon}) = 991.66 \text{ gallons}$. After the 5 mile-per-gallon improvement in fuel economy for each vehicle, NHTSA's estimate would decline to $(17,000 \text{ miles}/35 \text{ miles per gallon}) + (17,000 \text{ miles}/45 \text{ miles per gallon}) = 486 + 378 = 863.49 \text{ gallons}$, yielding an estimated fuel savings of $991.66 \text{ gallons} - 863.49 \text{ gallons} = 128.17 \text{ gallons}$.

⁶⁸⁹ For example, some businesses, taxi operators, and ride sharing drivers are likely to anticipate using their vehicles significantly more than the average new car or light truck 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.

evaluating the change in spending from requiring the change in standards 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 \$1,700.00 (calculated as 17,000 miles / 40 mpg 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 \$1,133.22 (calculated as 17,000 miles / 30 mpg x \$2.00 per gallon), so total annual fuel costs for these two vehicles will be \$1,700 + \$1,133.33 = \$2,833.33. If the fuel economy of both vehicles increases by 5 mpg, their actual total fuel savings will be \$2833.33 - \$2482.54 = \$350.79. However, evaluating total fuel savings using an average price of \$3.00 per gallon yields savings of \$2975-\$2590.48 = \$384.52, thus overstating their actual combined difference in spending by over 9 percent.

Both biases are consistent, in that the agency's analysis is also likely to overestimate the increase in fuel consumption and costs from imposing less stringent fuel economy standards. In the above example, reducing the fuel economy of each of the two vehicles by 5 mpg (to 25 and 35 mpg) would increase their combined actual fuel consumption by 165 gallons, but assuming each is driven the average number of miles per year yields an increase of 174 gallons, an overestimate of almost 6 percent. Similarly, using the nationwide average fuel price to value the increase in fuel consumption and costs would overestimate the increase in the latter by more than 10 percent.

6.1.5. Impacts on Refueling Frequency

CAFE standards affect the amount of time drivers spend refueling their vehicles in two ways. First, standards change the fuel economy of ICE vehicles produced in the future, which affects their maximum driving range before requiring refueling and thus changes the frequency with which most drivers refuel them.⁶⁹⁰ Second, standards can affect the purchase price of new vehicles. To the extent that more stringent standards increase the purchase prices of new vehicles, they may reduce sales of new vehicles and slow the retirement of used ones. This causes more VMT to be driven by older, less efficient vehicles that require more frequent refueling for the same amount of use. Conversely, reducing the stringency of standards would lower new vehicle prices, increasing both new vehicle sales and retirement of older vehicles, leading to a more efficient vehicle fleet and less frequent refueling. The basic calculation for both effects is the same: NHTSA multiplies the amount of time spent refueling by the collective value of time for vehicles' occupants and calculates the difference in this total value between the baseline and each regulatory alternative to determine the latter's effect.

6.1.5.1. Value of Travel Time Savings

The calculation of the value of vehicle occupants' time follows guidance from DOT's 2016 *Value of Travel Time Savings* memorandum ("VTTS Memo"), as updated for DOT's December 2025 Benefit-Cost Analysis Guidance for Discretionary Grant Programs ("BCA Guidance").⁶⁹¹ The economic value of

⁶⁹⁰ Some drivers refuel their vehicles on a regular schedule rather than in response to running low on fuel, so increasing their vehicles' driving range will not affect the frequency with which they purchase fuel.

⁶⁹¹ DOT, The Value of Travel Time Savings: Departmental Guidance for Conducting Economic Evaluations, Revision 2, Departmental Guidance on Valuation of Travel Time in Economic Analysis, DOT: Washington, D.C. (2016), available at: <https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-valuation-travel-time-economic> (accessed: May 22, 2026); DOT, Benefit-Cost Analysis Guidance for Discretionary Grant Programs, DOT: Washington, D.C. (December 2025), available at: <https://www.transportation.gov/sites/dot.gov/files/2025-12/Benefit%20Cost%20Analysis%20Guidance%202026%20Update%20%28Final%29.pdf> (accessed: May 22, 2026).

refueling time savings is calculated by applying vehicle occupants’ valuation of travel time savings recommended in the VTTS Memo and BCA Guidance to estimates of how much time is required to refuel vehicles under the baseline and each regulatory alternative. The average hourly value of occupants’ travel time depends on hourly valuations of personal and business time, which in turn depend on annual household income and total hourly compensation costs to employers, respectively. The total value of vehicle occupants’ time spent refueling also depends on the average number of passengers the vehicle is carrying, because their time—as well as the vehicle’s driver—entails an economic value or cost.

Table 6-2 demonstrates NHTSA’s approach to estimating the value of vehicle occupants’ travel time (in \$ per person-hour) for urban and rural driving, which are subsequently combined to yield overall average values. NHTSA makes the simplifying assumptions that urban travel consists entirely of local trips, while travel in rural areas is assumed to consist of exclusively longer distance intercity travel. DOT’s guidance assigns a lower hourly valuation to personal travel time than to business travel time and specifies separate distributions between personal and business travel in urban and rural areas.⁶⁹² Values reported in DOT’s most recent BCA Guidance are denominated in 2024 dollars.

Table 6-4: Value of Travel Time in Urban and Rural Travel (2024\$/person-hour)

	Personal Travel	Business Travel	Total
Urban (Local) Travel			
Hourly Valuation	\$20.10	\$34.60	-
% of Total Urban Travel	88.2%	11.8%	100%
Contribution to Total Hourly Valuation (Adjusted for % of Urban Travel)	\$17.70	\$4.10	\$21.80
Rural (Intercity) Travel			
Hourly Valuation	\$28.20	\$34.60	
% of Total Rural Travel	78.6%	21.4%	100%
Contribution to Hourly Valuation (Adjusted for % of Total Rural Travel)	\$22.20	\$7.40	\$29.60

Estimates of the hourly values of urban and rural travel time (\$21.80 and \$29.60) shown in Table 6-2 are then combined using the nationwide distribution of urban vs. rural driving to yield an overall average hourly value of occupants’ time, as shown in Table 6-5.⁶⁹³

⁶⁹² 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).

⁶⁹³ Proportions of urban and rural travel calculated from FHWA Highway Statistics, 2024, Table VM-1 (Light-Duty Vehicles Only): Annual Vehicle Distance Traveled (2024), available at: <https://www.fhwa.dot.gov/policyinformation/statistics/2024/pdf/vm1.pdf> (accessed: May 22, 2026).

Table 6-5: Weighted Average Value of Travel Time (2024\$/person-hour)

Location	Value of Travel Time (2024\$/person-hour)	Weight (% of Total Miles Driven)	Weighted Value of Travel Time (2024\$/person-hour)
Urban Travel	\$21.80	70.8%	\$15.40
Rural Travel	\$29.60	29.2%	\$8.60
Total	-	100.0%	\$24.00

The values reported in Table 6-5 represent the hourly values of travel time for each vehicle occupant, and many vehicles carry passengers as well as their driver, all of whom are delayed during refueling stops. To estimate the average value of travel time per vehicle-hour, Table 6-6 accounts for all vehicle passengers, using estimates of average vehicle occupancy tabulated from the 2022 National Household Travel Survey.^{694,695}

Table 6-6: Estimating the Value of Travel Time for Light-Duty Vehicles (\$/hour, 2024\$)

	Passenger Cars	Light Trucks
Average Vehicle Occupancy During Refueling Trips (persons)	1.39	1.67
Weighted Value of Travel Time (\$/hour)	\$24.00	\$24.00
Occupancy-Adjusted Value of Vehicle Travel Time During Refueling Trips (\$/hour)	\$33.40	\$40.10

6.1.5.2. The Effect of Fuel Economy on Refueling Frequency and Time

The CAFE Model calculates the number of refueling events for each vehicle in a calendar year by dividing the number of miles it is driven by the product of its on-road fuel economy (rather than its fuel economy as measured for compliance purposes), the capacity of its fuel tank, and the estimated fraction of the tank filled during each refueling event, as shown in Equation 6-2.

Equation 6-2: Calculating the Number of Refueling Events

$$Refuel\ Events_{CY, Veh} = \frac{Miles_{CY, Veh}}{FE_{Veh} * Tank_{Veh} * Share_{Veh}}$$

As the equation suggests, higher fuel economy reduces the frequency of refueling events, while lower fuel economy increases their frequency. The model then computes the annual cost of refueling time as the product of the annual number of refueling events, the total each event requires, and the total value of its occupants' time, as shown in Equation 6-3.

⁶⁹⁴ The National Household Travel Survey excludes trips by children under age 5.

⁶⁹⁵ The average occupancy estimates reported in Table 6-4 are consistent with occupancy assumptions used to estimate the social cost of additional traffic congestion in Chapter 6.2.3 below.

Equation 6-3: Calculating the Cost of Refueling Events

$$Cost_{CY, Veh} = Refuel\ Events_{CY, Veh} * (Event\ Time_{Veh}) * Time\ Value$$

The duration of refueling events for each vehicle is calculated by summing a fixed and variable component. The fixed component represents the time required to locate and travel to a refueling station, which is independent of a vehicle's tank size and share refueled. The variable component is the time required to refuel the tank itself, calculated as the number of gallons purchased at each refueling event— itself the product of the tank size and share refueled—divided by the rate at which fuel flows 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 fixed time component, share refueled, and rate of flow are calculated from survey data gathered as part of NHTSA's 2010-2011 National Automotive Sampling System's (NASS) Tire Pressure Monitoring System (TPMS) study.⁶⁹⁶ Finally, vehicle fuel tank sizes are taken from manufacturer specifications for the reference fleet, and historical averages are calculated from popular models in the current vehicle fleet.

NHTSA estimated the amount of time saved from less frequent refueling using survey data gathered as part of the 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 traveled to and from fueling stations, the time required to do so, and how many gallons of fuel they purchased. The TPMS survey includes light-duty passenger vehicles, sport utility vehicles, van-based light trucks, and light convenience trucks.

NHTSA 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 the time required to refuel their vehicles and complete the transaction at the filling station. For drivers who refuel on a regular schedule, during incidental stops, or for other reasons (e.g., using restrooms or buying snacks), the frequency of refueling is unlikely to be affected by fuel economy improvements. This restriction was imposed to exclude potentially distorting effects of those who refuel on a fixed (e.g., weekly) schedule and are unlikely to alter refueling patterns as a result of increased driving range.⁶⁹⁷ Table 6-7 presents TPMS survey data on average characteristics of refueling trips.

Table 6-7: Average Refueling Trip Characteristics for Passenger Cars and Light Trucks

	Fuel Purchased (gallons)	Round-Trip Distance to Fuel Station (miles)	Round Trip to Fuel Station (minutes)	Pay for Fuel and misc. (minutes)	Refueling (minutes)	Total Time (minutes)

⁶⁹⁶ See Peer Review of NHTSA/NASS Tire Pressure Monitoring System (TPMS), NHSTA, Docket No. NHTSA-2012-0001.

⁶⁹⁷ 36 percent of TPMS respondents stated they refuel on a regular schedule, during incidental stops, or for reasons unrelated to a low reading on the gas gauge. These respondents will not experience refueling benefit since their behavior is unlikely to be impacted by changes in fuel economy. The analysis of refueling trip characteristics excludes data from this category of driver.

			fixed	fixed	variable	
Passenger Cars (PCs)	10	1.0	2.3	1.2	2.9	6.4
Light Trucks (LTs)	13	1.1	2.5	1.2	3.1	6.8

The calculations described above are repeated for each future calendar year in the analysis. As a vehicle ages, the benefit from less frequent refueling attributable to it declines because vehicles are driven less as they age, so they consume less fuel and require less frequent refueling.⁶⁹⁸ More stringent regulatory alternatives cause fleet turnover to slow, so older and less efficient vehicles are relied upon to drive additional miles, and this shift of VMT from newer to older vehicles offsets a portion of the refueling benefit that would otherwise result from imposing stricter CAFE standards. Conversely, less stringent alternatives promote fleet turnover, causing VMT to shift from older vehicles to more efficient, newer vehicles, increasing the refueling benefit.

The CAFE Model tracks the legacy fleet of LDVs by body style and vintage, using average measures for fuel economy. Estimating refueling costs for these vehicles require measures of average fuel tank sizes by body style and vintage. NHTSA used publicly available data on fuel tank sizes of 17 high-volume nameplates to derive estimates of average fuel tank size for past model years.⁶⁹⁹ 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 CAFE Model then uses the fuel tank sizes to determine the number of refueling events and time spent refueling to compute refueling costs using the methodology described above.

After calculating the aggregate value of refueling time under each regulatory alternative for both the new and legacy fleets using the procedure and inputs described above, the Model calculates the incremental change relative to the baseline to estimate the refueling cost or benefit for that regulatory alternative.

6.1.6. Mobility Impacts

Requiring new cars and light trucks to achieve higher fuel economy reduces their fuel costs for driving each mile, and the number of miles their buyers drive rises slightly in response due to the well-documented fuel economy rebound effect. If buyers of new vehicles elect to drive more, the benefits from doing so must be large enough to offset the cost of fuel consumed in traveling those additional miles.⁷⁰⁰ Because the cost of fuel consumed by this additional, rebound-effect driving has already been accounted for as part of the change in fuel expenditures under each regulatory alternative, it is necessary to account for the offsetting benefits associated with those additional miles traveled.⁷⁰¹

The amount by which the benefits of this rebound-effect travel *exceed* its economic costs, usually referred to as increased consumer surplus, measures the net benefits drivers and their passengers experience from their additional travel. Conversely, should drivers and their passengers elect to travel fewer miles when new vehicles feature lower fuel economy and higher fuel costs, the benefits of any additional driving must be insufficient to outweigh its fuel costs.

⁶⁹⁸ See Chapter 4.3.2.

⁶⁹⁹ 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.

⁷⁰⁰ This follows from the theory of revealed preference. Conditional on already owning a vehicle and assuming consumers have some knowledge of fuel costs, the benefit they receive of driving an additional mile must outweigh the fuel costs associated with that mile (the private benefit is greater than the private cost). This is ‘revealed’ to be true, otherwise the consumer would not choose to drive that additional mile because doing so would result in a welfare loss.

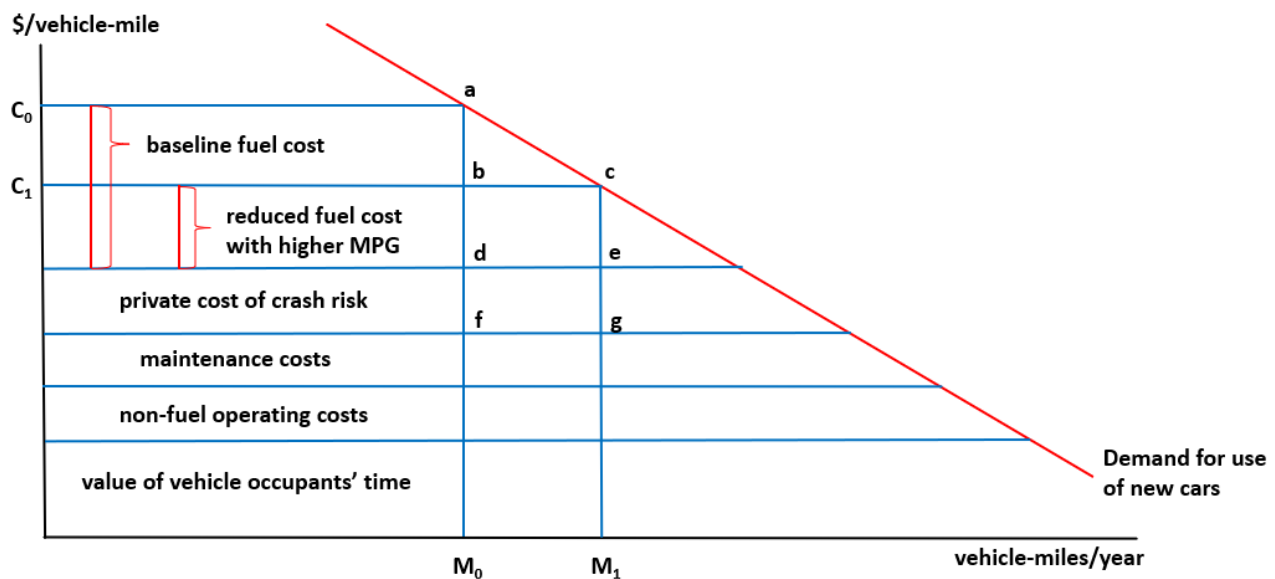
⁷⁰¹ The benefits from additional travel must also offset the economic value of their (and their passengers’) travel time, other vehicle operating costs, and the economic cost of safety risks due to the increase in exposure that occurs with additional travel.

Figure 6-4 below illustrates the mobility benefit of raising CAFE standards and reducing new cars' and light truck fuel costs. Requiring higher fuel economy reduces the cost of fuel per mile driven, which in turn reduces the total cost of driving each mile from C_0 to C_1 , prompting an increase in their annual use from M_0 to M_1 . Total benefits from the additional driving are equal to the area M_0 -a-c- M_1 , of which the rectangle M_0 -b-c- M_1 represents costs, leaving the triangle a-b-c as a gain in consumer surplus to drivers and their passengers. The area of the rectangle b-c-e-d represents the cost of the fuel consumed by driving those additional miles.⁷⁰² When standards are decreased as is the case in this Final rule, annual use declines relative to the amount of driving done under higher standards. This is caused by an increase in the cost of driving, and results in a reduction in benefits equivalent in size to the same area M_0 -a-c- M_1 .

The rectangle d-e-f-g represents their “expected” cost from increased exposure to the risk of being involved in a crash, since driving more miles increases that risk proportionally. Like the cost of fuel used to drive additional miles, this added risk must be offset by benefits of additional travel, or those trips would not be made. While the agency assumes that drivers consider the added safety risks they assume when undertaking additional trips, NHTSA does not believe that they fully internalize the risks they impose on *other drivers* when they travel more. Thus, unlike fuel costs, where the corresponding benefit associated with the additional fuel cost of rebound-effect travel fully offsets its increased cost, the agency assumes that benefits from additional travel offset only 90 percent of the increased safety risks. This issue is discussed further in Chapter 7.5.

While Figure 6-4 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 NHTSA does not estimate these costs of increased driving, there is no need to account for offsetting benefits separately as the agency does with fuel costs and safety risks of added rebound-effect travel.

Figure 6-4: The Benefit of Additional Mobility



⁷⁰² The CAFE Model tracks mileage accrual for new vehicles at a very granular 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.

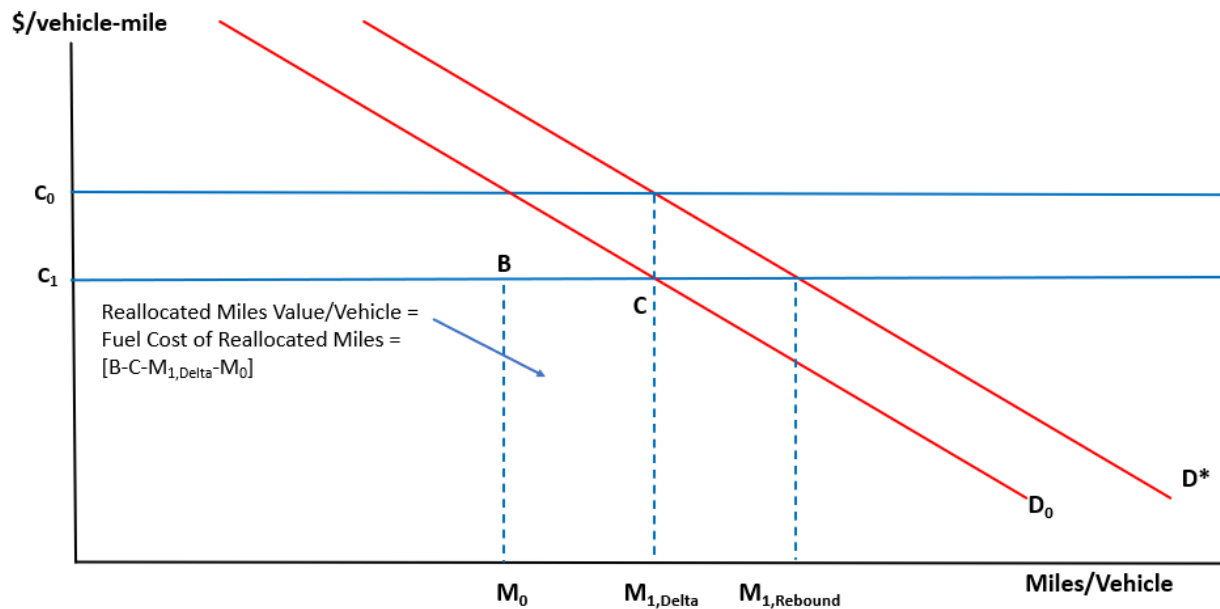
CAFE standards alter the number of new vehicles sold in each future model year they affect. When future vehicle sales under a regulatory alternative differ from their level projected under the baseline, the CAFE Model adjusts average annual miles traveled for each vehicle type, model year, and age to ensure that the total number of miles traveled (prior to considering the fuel economy rebound effect) is identical under each alternative (see Chapter 4.3.2). When new vehicle sales decline relative to the baseline, the average number of miles driven annually per vehicle increases, because the same total number of miles per year is assumed to be driven using fewer vehicles. This effect also operates in reverse when vehicle sales increase from their baseline quantities, reducing the average number of miles driven annually by each vehicle.

Reallocating some VMT to vehicles produced during previous model years implies that consumers are willing to incur their higher fuel and other operating costs to continue making trips they would otherwise have made in new vehicles. Again, this implies that the benefits those trips provide are sufficient to offset the added fuel and other operating costs, though estimating the corresponding benefit complicates the analysis somewhat.

Figure 6-5 illustrates the consumer benefit in question. In the figure, D_0 is the per-vehicle travel demand curve in the baseline. An alternative that imposes higher CAFE standards results in new vehicle sales declining relative to the baseline, thus reallocating a quantity of miles to the smaller number of vehicles that continue to be sold. This in effect shifts the VMT demand curve for individual vehicles' use outward to D^* (a larger number of miles per vehicle for a given CPM, equal to $(M_{1,\Delta} - M_0)$ reallocated miles). At the same time, a higher CAFE standard results in a lower average CPM, a change equal to $C_1 - C_0$. Combining these two impacts, the expenditure for the reallocated miles is equal to the reallocated miles times the average CPM under that alternative (*i.e.*, by the dollar value of the rectangle $(M_{1,\Delta} - M_0) * C_1$). Finally, the increase in vehicle-miles due to the rebound effect of lower fuel costs ($C_1 < C_0$) leads to a further increase of miles per vehicle along the D^* curve to $M_{1,\text{Rebound}}$. The resulting costs from this rebound effect are equal to the dollar value of the rectangle with area equal to $(M_{1,\text{Rebound}} - M_{1,\Delta}) * C_1$.

Both sources of this 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 any changes in the benefits from driving these reallocated miles in the analysis, since the fuel costs for driving them are already incorporated in the calculated fuel spending.

Figure 6-5: Per Vehicle Change in Vehicle Travel as a Function of Cost per Mile



In the case where the stringency of fuel economy standards is reduced, sales of new vehicles increase relative to the baseline alternative, reallocating VMT away from older vehicles to new ones. Again, this implies that consumers are willing to incur the higher per-mile costs of driving newer vehicles, indicating that the benefits they provide are sufficient to outweigh their higher fuel costs. The method for estimating this is the same as described above, except in the opposing direction; that is, the benefit of the reallocated VMT is assumed to be at least equal to the quantity of miles reallocated to newer vehicle multiplied by the cost of driving each additional mile.

Because total non-rebound VMT is restricted to be identical under the baseline and regulatory alternatives, there is no change in consumer surplus due to the reallocation of miles under any of those alternatives. For this reason, NHTSA calculates only the fraction of the value of reallocated miles that corresponds to the changing fuel cost of driving those incremental miles, and assumes that it exactly offsets the resulting change in fuel costs.⁷⁰³ This “mobility value” of reallocated mileage is calculated as the product of VMT reallocated under each alternative and the cost of fuel per mile under that alternative, shown in Figure 6-5 as the area $(M_{1,\Delta} - M_0)C_1$, and it again exactly offsets the change in fuel costs.⁷⁰⁴ A detailed explanation of the method used for this calculation is available in the CAFE Model Documentation, Section S8.8.2.

In contrast to the social cost-benefit analysis, the 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. This adjustment to account for the additional fuel costs and offsetting benefits of reallocated miles is specific to

⁷⁰³ By reallocating every mile that would have been traveled by the vehicles not sold (in the case of a reduction in new vehicle sales), NHTSA implicitly assumes 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 NHTSA implicitly assumes there is no change in consumers’ welfare due to the reallocation. For this reason, NHTSA does 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.

⁷⁰⁴ See Chapters 4.3.1 and 4.3.2 for a description of how VMT is reallocated in the baseline.

the calculation of the per-vehicle value of mobility and does not affect the social costs or benefits of alternative changes in CAFE standards.

6.2. Other Benefits, Costs, and Impacts

In addition to the benefits and costs that establishing CAFE standards creates for manufacturers and buyers of new vehicles, NHTSA's analysis evaluates several impacts its final rule will have on the public and the U.S. economy. The agency refers to these indirect impacts as "external" costs and benefits from changing the stringency of standards, because they extend beyond the private businesses and households that experience the more direct effects of changing CAFE standards.

One external impact from increased fuel consumption is higher emissions of air pollutants and the consequent increase in health impacts from exposure to air pollution. Chapter 5.2 and Chapter 5.3 explain how the agency estimates the changes in emissions of pollutants that are likely to result from changes to the CAFE standards. Chapter 6.2.1 explains how the agency treats the associated changes in future pollutant-related economic damages, while Chapter 6.2.2 explains how NHTSA estimates the economic value of changes in health outcomes due to emissions.

Chapter 4.3.5 describes how CAFE standards influence the number of miles that vehicles are driven, via the fuel economy rebound effect. This additional driving contributes to traffic congestion and road noise, the effects of which will extend to other road users as well as to residents of areas surrounding streets and highways. Chapter 6.2.3 explains how NHTSA estimates changes to congestion and noise externalities.

Chapter 6.2.4 discusses how U.S. consumption and imports of petroleum generate economic externalities that may impose potential costs beyond those borne by consumers of petroleum products. In addition, Chapter 6.2.4 describes how increasing gasoline consumption may contribute to these external costs.

Chapter 6.2.5 discusses how CAFE standards affect automotive labor hours. The costs associated with increases or decreases in labor are captured by the changes in regulatory costs. However, NHTSA evaluates changes in labor utilization independently as an additional impact of CAFE standards, separate from the cost-benefit analysis.

A 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, pedestrians, and bystanders using the same roads. Chapter 7.5 describes how the agency estimates this "external" component of safety risks from additional rebound-effect driving and discusses 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, setting standards that change fuel consumption affects the amount of fuel tax revenue collected by government agencies. Fuel taxes represent transfers from drivers to government agencies. The change in fuel taxes paid by drivers is included in the private costs above with the estimation of fuel savings. The corresponding change in revenue collected by governments is added as an external benefit. Since the two are transfers, the change in consumer costs and benefits to governments are equal which results in no net change in societal welfare.

6.2.1. Valuation of Carbon Emissions

The combustion of petroleum-based fuels that power cars and light trucks generate emissions of CO₂ and other non-criteria pollutants. The processes of extracting and transporting crude petroleum, refining it to produce transportation fuels, and distributing fuel for retail sale also generate additional carbon emissions ("upstream" emissions). By altering the volume of petroleum-based fuel produced and consumed by cars

and light trucks, the standards this rule finalizes affect both direct carbon emissions from vehicles' fuel consumption and upstream emissions from supplying petroleum-based fuels. NHTSA does not include a valuation of carbon emissions in its central analysis, as described in Preamble II.G, but Chapter 9 of the FRIA includes a sensitivity analysis that values resulting changes in emissions of CO₂ based on values applied in the FRIA for the SAFE final rule. For an extensive discussion of the definitions, sources, and impacts of these emissions, see Chapter 5 of the Final SEIS accompanying the final rule. Final TSD Chapter 5 details how NHTSA estimates changes in emissions resulting from the different rulemaking alternatives it considers.

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 PM_{2.5} and two precursors to PM_{2.5} (NO_x and SO₂). Chapter 5 discusses how EPA currently regulates other criteria pollutants, such as CO and ground-level ozone (O₃). NHTSA calculates impacts solely from these three pollutants because they are known to be emitted regularly from mobile sources and have the most adverse effects to human health. 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 BPT estimates for these pollutants. The CAFE Model computes the monetized impacts associated with health impacts 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 EFs 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. NHTSA used the same EPA sources that provide health incidence values to determine which monetized health impacts per ton values to use as inputs in the CAFE Model. EPA uses a 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.⁷⁰⁵ EPA's 2018 TSD "Estimating the Benefit per Ton of Reducing PM_{2.5} Precursors from 17 Sectors,"^{706,707} 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. NHTSA refers 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.

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, and electricity generation). 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

⁷⁰⁵ Though 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.

⁷⁰⁶ Office of Air and Radiation and Office of Air Quality Planning and Standards, Estimating the Benefit per Ton of Reducing PM_{2.5} Precursors from 17 Sectors, EPA: Research Triangle Park, NC, pp. 1 – 105 (2018), available at: https://www.epa.gov/sites/default/files/2018-02/documents/sourceapportionmentbptsd_2018.pdf (accessed: May 22, 2026) (hereinafter, "Office of Air and Radiation (2018)").

⁷⁰⁷ Referred to here as the 2018 EPA source apportionment TSD.

differences in the geographic distribution of the pollutants—a factor that affects the number of people impacted by the pollutants.⁷⁰⁸

The various emission source sectors included in the cited EPA papers do not always correspond to the emission source categories used in the CAFE Model.⁷⁰⁹ In those cases, NHTSA maps multiple EPA sectors to a single CAFE source category and computes 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 reports benefits per ton values for the years 2020, 2025, and 2030. For the years between source years used in the input structure, the CAFE Model applies values from the closest source year. For instance, the Model applies 2025 values for CYs 2023-2027 and 2030 values for CYs 2028-2032. For more information, see the CAFE Model Documentation, which contains additional details of the CAFE Model’s computation of monetized health impacts.

Though EPA has published new health impact per ton values recently for various sectors, including refineries, oil and gas, and electricity-generating units, NHTSA does not use these in its analysis since the new estimates are not available for all sectors. Switching to the values that use the latest EPA methodology would require leaving out multiple pollutant sectors from NHTSA’s analysis (petroleum transportation, fuel transportation, storage and distribution, and mobile source sectors). While the older BPT values in NHTSA’s analysis may undervalue the benefits of reducing criteria pollutant emissions slightly, removing these categories also would undervalue criteria pollutant 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 health benefits related to PM_{2.5} and uncertainties associated with the BPT approach are discussed above in Chapter 5.4.2.

The following subchapters describe the sources that NHTSA uses to provide the CAFE Model with values for monetized health impacts per ton 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 TS&D
- Electricity Generation

⁷⁰⁸ Office of Air and Radiation (2018).

⁷⁰⁹ The CAFE Model’s emission source sectors follow a similar structure to the inputs from GREET. See Chapter 5.2 for further information.

Downstream emissions sources

On-road LD cars and motorcycles

On-road LD trucks

On-road LD diesel

Table 6-7 details how NHTSA maps between the CAFE Model and EPA emission source sectors. CAFE Model source sectors are based on categories of emissions from GREET, Argonne’s energy and vehicles life-cycle analysis model.

Table 6-8: 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 <i>et al.</i>). ⁷¹⁰
Petroleum Transportation	Assigned to several mobile source sectors from a 2019 EPA paper (Wolfe <i>et al.</i>)⁷¹¹ and one source sector from the 2018 EPA source apportionment TSD.⁷¹² The specific mode mappings are as follows: From Wolfe <i>et al.</i>: • 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 <i>et al.</i>)⁷¹³ and one source sector from the 2018 EPA source apportionment TSD. The specific mode mappings are as follows: From Wolfe <i>et al.</i>: • 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.

⁷¹⁰ Fann *et al.* (2018).

⁷¹¹ Wolfe *et al.* (2019). Health incidence per ton values corresponding to this paper were sent by EPA staff.

⁷¹² Office of Air and Radiation (2018).

⁷¹³ Wolfe *et al.* (2019).

Electricity Generation	Assigned to the electricity-generating units' sector from the 2018 EPA source apportionment TSD. ⁷¹⁴
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6.2.2.1. Petroleum Extraction Sector

NHTSA matches the monetized health impact per ton values for the petroleum extraction sector with a 2018 oil and natural gas sector paper (Fann *et al.*). This paper estimates monetized health impacts for this sector in the year 2025.⁷¹⁵ Fann *et al.* define emissions from the oil and natural gas sector not only as arising from petroleum extraction, but also from transportation to refineries, while the CAFE/GREET component is composed of only petroleum extraction. NHTSA consulted with the authors of the EPA 2018 TSD and determined that this paper (Fann *et al.*) contains the best available estimates for the petroleum extraction sector, notwithstanding this difference. Therefore, these monetized values may overestimate the cost of health impacts associated with emissions from this sector slightly.

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.⁷¹⁶ To match the structure of other health impact costs in the CAFE Model, NHTSA 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 resembles the petroleum extraction sector in emission location characteristics, as both occur largely in rural areas.⁷¹⁷

Fann *et al.* estimated monetized health impacts per ton values only for CY 2025, so NHTSA applied these values to all the years in the CAFE Model health impacts input structure: 2025 and 2030.⁷¹⁸ 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 dollars. NHTSA uses implicit price deflators from BEA to convert the estimates to 2024 dollars to be consistent with the rest of the CAFE Model inputs.⁷¹⁹

6.2.2.2. Petroleum Transportation Sector

NHTSA uses 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 NHTSA uses a weighted average of multiple EPA sectors to determine the monetized health impact per ton values for the petroleum transportation sector as a whole. In calculating the weighted average, NHTSA mapped the petroleum transportation sector as described in GREET 2025 to a combination of different EPA mobile

⁷¹⁴ Office of Air and Radiation (2018).

⁷¹⁵ Fann *et al.* (2018).

⁷¹⁶ *Id.*

⁷¹⁷ Office of Air and Radiation (2018).

⁷¹⁸ These 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.

⁷¹⁹ BEA, Table 1.1.9, Implicit Price Deflators for Gross Domestic Product, available at: <https://www.bea.gov/tools> (accessed: May 22, 2026).

source sectors from two different papers, the 2018 EPA source apportionment TSD⁷²⁰ and a 2019 mobile source sectors paper (Wolfe *et al.*).⁷²¹ See Table 6-8 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, NHTSA uses sectors from Wolfe *et al.* wherever possible and uses the 2018 EPA source apportionment TSD for the transportation mode mapping only when there are no appropriate sectors in Wolfe *et al.* Also, Wolfe *et al.* only reports impacts for the year 2025, but after communication with one of the authors at EPA, NHTSA determined that these values could be applied to the other years in the input structure. Therefore, this implies a slight underestimation of monetized impacts in 2030.

NHTSA calculates 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 6-9: Petroleum Transportation Mode Shares in 2025⁷²²

Fuel Type ⁷²³	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 percentage of these five petroleum products transported by each mode, as shown in Table 6-9. 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

⁷²⁰ Office of Air and Radiation (2018).

⁷²¹ Wolfe *et al.* (2019).

⁷²² 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.anl.gov/> to download the model.

⁷²³ 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.

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. NHTSA multiplied these emissions values by the percentage of petroleum product transported by each mode, as seen in Table 6-9, 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. In addition, 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.

NHTSA multiplies 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 2025 and 2030, based on the mode percentages GREET reports for those years.⁷²⁴

Table 6-10: Energy Share by Petroleum Type⁷²⁵

Conventional Crude Oil	SCO	Dilbit	Shale (Bakken)	Shale (Eagle Ford)
79.1%	3.5%	5%	6.5%	5.9%

NHTSA then multiplies 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 6-10, NHTSA multiplies 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, NHTSA sums the resulting weighted emissions values by pollutant to represent the total upstream emissions in grams/mmBTU of petroleum product transported. With that information, NHTSA can calculate the percentages of each pollutant attributable to each mode for petroleum transportation overall. NHTSA calculated these percentages three times, for each different base year (2025 and 2030); Table 6-11 shows these percentages, using base year 2025 as an example.

Table 6-11: Percent of Emissions Attributable to Each Mode for the Petroleum Transportation Category⁷²⁶

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%

⁷²⁴ These are the two 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.

⁷²⁵ Taken from the Petroleum tab of the GREET Excel Model, using 2025 as a base year.

⁷²⁶ These percentages are calculated using the 2025 base year in GREET.

Finally, NHTSA calculates 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 6-5 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 6-5: Weighted Average of Health Incidences from the Petroleum Transportation Sector

Asthma Exacerbation incidents per ton from SO_x in Petroleum Transportation=

$$(\%SO_x \text{ ocean tanker} \times C3\text{marine}) + (\%SO_x \text{ barge} \times C1\&C2 \text{ marine}) + \\ (\%SO_x \text{ pipeline} \times EGU) + (\%SO_x \text{ rail} \times \text{Rail}) + (\%SO_x \text{ truck} \times \text{Truck})$$

Following guidance from the 2018 EPA source apportionment TSD, NHTSA rounds the final health impact costs per ton to two significant digits.⁷²⁷

6.2.2.3. 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 because NHTSA calculates 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 NHTSA 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. NHTSA maps 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.*⁷²⁸

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 multiple modes are taken during the distinct parts of the trip. As an example, Table 6-12 shows the estimated mode shares in 2025.

⁷²⁷ Office of Air and Radiation (2018).

⁷²⁸ Office of Air and Radiation (2019); Wolfe, P. *et al.*, 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 (2019), available at: <https://pubmed.ncbi.nlm.nih.gov/30296769/> (accessed: May 22, 2026).

Table 6-12: Transportation Mode Shares for the Fuel TS&D Sector⁷²⁹

Mode Share	Gasoline Blendstocks	Finished Gasoline
Ocean Tanker	0.0%	-
Barge	31.2%	-
Pipeline	66.6%	-
Rail	2.2%	-
Truck	100%	100%

NHTSA multiplies the emissions by pollutant attributed to each mode (measured in grams/mmBTU) by these mode share percentages to create weighted emissions values.

Next, NHTSA adds the weighted emissions from trucks transporting gasoline blendstocks to the emissions arising from finished gasoline transportation (100 percent truck mode). Using that information, NHTSA calculates the total emissions per pollutant to find the percentage of emissions attributable to each mode for fuel TS&D overall. Table 6-13 provides an example of these percentages.

Table 6-13: Percent of Emissions Attributable to Each Mode for the Fuel TS&D Category⁷³⁰

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	68.08%	7.95%	71.79%
Pipeline	Electricity-generating units	6.24%	79.34%	16.72%
Rail	Rail	0.81%	0.15%	0.47%
Truck	On-road heavy-duty diesel	24.87%	12.56%	11.02%

NHTSA follows 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. NHTSA completed these calculations for years 2025 and 2030.⁷³¹ As stated previously, the sectors in the 2019 mobile sources paper only showed monetized health costs-per-ton estimated for the year 2025, but NHTSA determined that this information should be applied to all years, as it was the most up-to-date available.⁷³² The use of 2025 monetized impacts implies a slight underestimation in 2030.

Wolfe *et al.* reported all monetized impacts per ton values in 2015 dollars. NHTSA used BEA deflators to convert these values to 2024 dollars to ensure consistency with the rest of the CAFE Model inputs.⁷³³

6.2.2.4. Refineries Sector

NHTSA matches 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.

⁷²⁹ Using baseline year 2025 in GREET. These values can be found in the ‘T&D Flowcharts’ tab of the GREET Model.

⁷³⁰ These percentages are calculated using the 2025 base year in GREET.

⁷³¹ NHTSA uses 2025 for years 2024-2027 and 2030 values for 2028 and subsequent years.

⁷³² NHTSA communicated with an author of the paper at EPA to help inform NHTSA’s decision.

⁷³³ BEA, Table 1.1.9, Implicit Price Deflators for Gross Domestic Product, available at: <https://www.bea.gov/tools> (accessed: May 22, 2026).

NHTSA uses BEA deflators to convert the values to 2024 dollars.⁷³⁴ Table 6-14 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.⁷³⁵

Table 6-14: Monetized (2024\$) Health Impacts per Ton from Refineries, 3% Discount Rate⁷³⁶

Calendar Year	Upstream Emissions (Refineries Sector)		
	NO _x	SO _x	PM _{2.5}
2025	\$10,800	\$110,000	\$510,000
2030	\$12,000	\$120,000	\$550,000

6.2.2.5. 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 dollars. NHTSA maps these to the electricity generation sector in the CAFE Model and converted the values to 2024 dollars using BEA deflators to ensure consistency with the rest of the CAFE Model inputs.⁷³⁷ Table 6-15 shows the health effects per ton associated with the emissions of criteria pollutants from this sector.

Table 6-15: Monetized (2024\$) Health Impacts per Ton from Electricity-Generating Units, 3-Percent Discount Rate⁷³⁸

Calendar Year	Upstream Emissions (Electricity Generation Sector)		
	NO _x	SO _x	PM _{2.5}
2025	\$8,600	\$59,000	\$220,000
2030	\$9,300	\$63,000	\$230,000

6.2.2.6. 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. NHTSA 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 who co-authored the paper. NHTSA matches three LD 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,” and “on-road LD diesel.” Table 6-16 shows the monetized impacts by criteria pollutant for these categories.

⁷³⁴ *Id.*

⁷³⁵ Office of Air and Radiation, p. 14 (2018).

⁷³⁶ Based on the Krewski *et al.* values in the 2018 EPA TSD. See Section II.F of the preamble for further discussion of the BPT reporting.

⁷³⁷ BEA, Table 1.1.9, Implicit Price Deflators for Gross Domestic Product, available at: <https://www.bea.gov/tools> (accessed: May 22, 2026).

⁷³⁸ Based on the Krewski *et al.* values in the 2018 EPA TSD. See Section II.F of the preamble for further discussion of the BPT reporting.

As in the case of the other monetized impacts from Wolfe *et al.*, NHTSA uses BEA deflators to convert monetized values from 2015 dollars to 2024 dollars.⁷³⁹

Table 6-16: Monetized (2024\$) Impacts per Ton from Downstream Source Categories, 3% Discount Rate

	On-road LD gas cars	On-road LD gas trucks	On-road LD diesel
NO _x	\$9,200	\$8,300	\$7,400
SO _x	\$160,000	\$130,000	\$390,000
PM _{2.5}	\$900,000	\$760,000	\$620,000

The CAFE Model also calculates the criteria pollutant emissions resulting from BTW. These emissions are grouped with downstream emissions and monetized using the same BPT values.

6.2.3. Social Costs of Congestion and Noise

As discussed in Chapter 4.3.5, a vehicle’s fuel economy affects the number of miles its owner chooses to drive. When CAFE standards increase the fuel economy of new vehicles, their buyers drive them slightly more (the fuel economy “rebound effect”), and their additional use adds slightly to current levels of traffic congestion and roadway noise. The resulting increase in delays to vehicles traveling in congested traffic, together with the effects of noise on residents of areas surrounding roadways, are additional economic costs directly attributable to raising fuel economy standards. In contrast, reducing CAFE standards reduces aggregate VMT, and the resulting reductions in traffic congestion and vehicle noise represent cost savings.

Only a small fraction of the resulting changes in delay and noise will be experienced by buyers of new vehicles, whose decisions about how much more or less to drive—and where and when to do so—cause them. Because they will be borne predominantly by others, the agency’s analysis treats these changes in the costs of congestion delays and noise as external costs or benefits of fuel economy standards. These are distinguished from private costs or benefits, such as the changes in purchase prices buyers of new vehicles pay.

To estimate the economic costs associated with changes in congestion delays and roadway noise caused by the fuel economy rebound effect, the agency uses estimates of incremental (or “marginal”) congestion and noise costs from incremental variation in vehicle 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 congestion resulting from incremental growth in vehicle use and the delays it causes to drivers, passengers, and freight shipments. Symmetrically, those values also measure the savings in congestion costs from slight reductions in vehicle use, traffic congestion, and resulting delays.

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 *change* in congestion costs resulting from incremental variation in the number of VMT. When roads are already crowded, marginal congestion costs can be much higher than their average value. 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

⁷³⁹ BEA, Table 1.1.9, Implicit Price Deflators for Gross Domestic Product, available at: <https://www.bea.gov/tools> (accessed: May 22, 2026).

large. The same process operates in reverse: the marginal reduction in delay to each vehicle that results from a modest decline in traffic volumes is small but affects a large number of vehicles, so it can be significant in total. Consequently, the variation in congestion and delays associated with even modest changes in driving are far more than proportional to the changes in traffic levels 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 automobiles and the estimated economic value of annoyance and other adverse impacts from noise. These effects are experienced by residents of the surrounding area, pedestrians and other road users not riding in motor vehicles, and occupants of other vehicles exposed to road noise.

The agency is reducing the stringency of previously established fuel economy standards, so the number of miles new vehicles will be driven is likely to decline slightly under each alternative compared to their baseline usage. To calculate the incremental savings in congestion and noise costs caused by reduced driving, the agency multiplies FHWA’s “middle” estimates of marginal congestion and noise costs per mile of auto and light truck travel by the decline in new vehicle travel under each alternative. NHTSA has updated the original 1997 FHWA estimates of congestion costs to account for changes in travel activity and economic conditions since they were developed, as well as to express them in 2024 dollars for consistency with other economic inputs.

The main factor affecting marginal congestion costs from minor variations in driving is the relationship of traffic volumes to roadways’ vehicle-carrying capacity, because this determines how travel speeds and delays will change in response to incremental variation 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; conversely, a similarly minor reduction in traffic can increase travel speeds and reduce delays noticeably. The agency assumes that the contribution of small variations in traffic volumes to current congestion and delays has grown in proportion to the increase in annual vehicle-miles traveled per lane-mile on major U.S. highways—a measure of how fully U.S. roadways’ vehicle-carrying capacity is typically utilized—since 1997, the date of FHWA’s original estimates of marginal congestion costs. Other factors contributing to higher marginal costs of congestion since that time (and higher benefits of reducing it) include growth in the hourly economic value of drivers’ and passengers’ travel time. The agency estimates growth in the hourly cost of increased delays between 1997 and 2024 by combining escalation in the DOT-recommended value of occupants’ travel time with changes in the average occupancy of cars and light trucks.^{740,741}

Table 6-16 reports the changes in each of the factors contributing to increased congestion costs between 1997 and 2024. The agency applies these adjustments to FHWA’s 1997 estimates of marginal congestion costs to update their original values to approximate the change in congestion costs likely to result from more or less driving due to the fuel economy rebound effect driving under current travel conditions. Expressed in 2024 dollars for consistency with the other economic values used to analyze this final rule, the agency’s updated values of external congestion costs are \$0.122 per-vehicle-mile of increased travel by cars, and \$0.109 per additional vehicle-mile for light trucks.

⁷⁴⁰ 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/>.

⁷⁴¹ Some commenters on NHTSA’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 show an 18-percent increase in congestion levels (as approximated by annual vehicle-miles per lane-mile on roads and highways), while the other most widely cited source of congestion and delay estimates reports that they grew 44 percent in the Nation’s 101 largest urban areas and 37 percent in all 494 U.S. urban areas over that same period, so NHTSA’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/>.

Table 6-17: Factors Contributing to Increased Congestion Costs

Factor	1997 Value	Updated Value	Change
Annual VMT per Highway Lane-Mile	310,782	364,452	17%
Average Vehicle Occupancy (persons)	1.61	1.52	-5%
Hourly Value of Time per-Vehicle Occupant (all vehicles; 2024\$)	\$ 17.72	\$ 23.14	31%
All Factors Combined	--	--	45%

NHTSA adjusted FHWA’s 1997 estimate of marginal noise costs only to account for inflation since their original publication because little research was 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. NHTSA’s estimates of incremental congestion and noise costs from reduced car and light truck use are assumed to remain constant (in real or inflation-adjusted terms) throughout the analysis period. This assumption is likely to underestimate incremental savings in congestion and noise costs because baseline levels of congestion delays and vehicle noise are likely to continue growing in 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.” Increases in their magnitude are sometimes cited as potential social costs of increased U.S. demand for petroleum and refined products, such as gasoline, while reductions in these external costs are often included as benefits of reducing domestic petroleum demand via measures such as setting CAFE standards.

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 higher global prices for petroleum and refined products. If markets for petroleum and refined products are competitive, this is simply a transfer of resources that produces no change in global economic output or welfare.

As the United States has become a net exporter of petroleum, this transfer of revenue increasingly has been from global consumers of petroleum products to U.S. petroleum producers, so any price increase that results from increased domestic petroleum demand does not have overall welfare implications and the additional financial burden to U.S. consumers is captured by domestic producers in the United States rather than foreign producers. In fact, if the United States remains a net petroleum exporter (the AEO 2026 projects the Nation to be a net exporter of petroleum and other liquids through 2050),⁷⁴² the transfer from global consumers to petroleum producers created by higher world oil prices provides a net financial benefit to the U.S. economy. While uncertainty about the Nation’s long-term import-export balance makes it difficult to project precisely how this situation might change in response to variation in U.S. domestic consumption of petroleum products, 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.

⁷⁴² EIA, AEO 2026, last revised: Apr. 8, 2026, available at: <https://www.eia.gov/outlooks/aeo/> (accessed: May 22, 2026).

Second, 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 the exposure of other consumers to the risk of sudden price changes, so the expected economic cost of that increase in risk is often cited as an external cost of increased U.S. petroleum consumption.

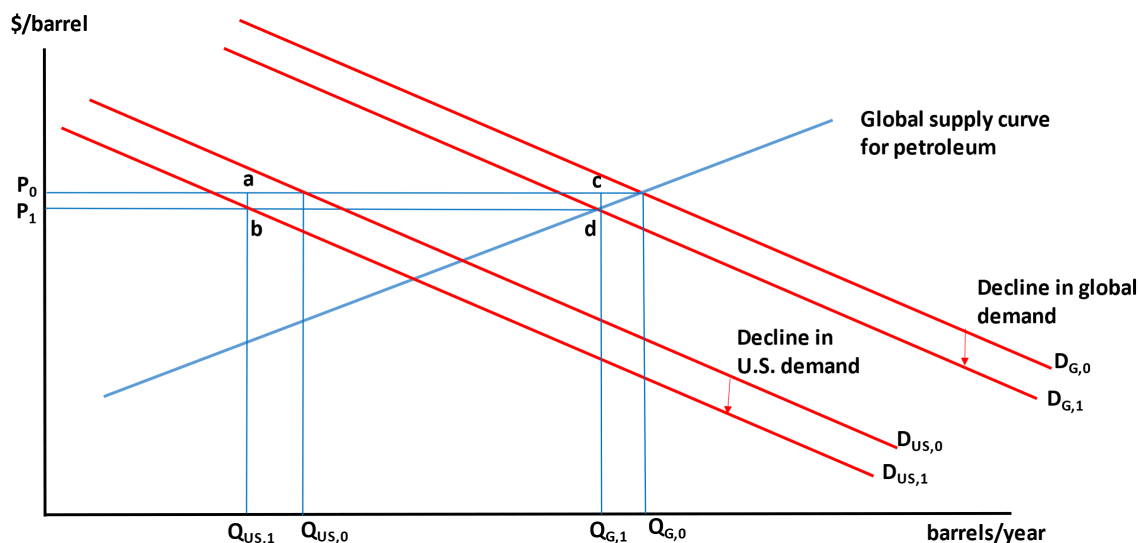
Finally, some analysts argue that domestic demand for imported petroleum may influence U.S. military spending; because any increase in the cost of military activities necessary to enable additional petroleum imports would not be reflected in retail gasoline prices this effect is often asserted to represent a third category of external costs from increased U.S. petroleum consumption.

This section assesses the extent to which each of these costs is likely to change because of changing the stringency of CAFE standards, identifies whether that change would represent a real economic benefit for the United States, and describes how the agency measures any resulting benefits or costs to incorporate in its analysis. NHTSA's current analysis quantifies the incremental effects of tightening or resetting fuel economy standards on costs related to energy security, and while these effects are likely to be modest, they can accumulate over a succession of changes in standards.

6.2.4.1. U.S. Petroleum Demand and its Effect on Global Prices

Figure 6-6 illustrates the effect of U.S. fuel and petroleum demand on worldwide demand for petroleum and its global market price under competitive market conditions, using the case of declining domestic demand as an example (exactly the reverse analysis would apply with increasing U.S. consumption). A reduction in domestic gasoline and petroleum demand from adopting CAFE standards is represented by an inward shift in the U.S. demand curve for petroleum from its initial position at $D_{US,0}$ without regulations, to $D_{US,1}$ with CAFE standards in effect. 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.⁷⁴³

Figure 6-6: U.S. Petroleum Demand and its Effect on Global Prices



⁷⁴³ The figure exaggerates the U.S. share of total global consumption, which currently stands at about 20 percent, for purposes of illustration.

The global supply curve for petroleum shown in Figure 6-7 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 to the world market.⁷⁴⁴ Thus the inward 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.⁷⁴⁵ 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 consists primarily 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 exact 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 global consumers also save that amount on each barrel they *continue* to buy. The resulting savings to U.S. domestic consumers 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 .^{746,747} These additional savings—sometimes termed the “monopsony effect” of U.S. petroleum consumption, in reference to the Nation’s large role in the global oil market—are sometimes cited as an economic benefit of measures, such as setting CAFE standards. However, it is interpreted more properly as reducing the transfer of revenue from U.S. consumers to domestic and foreign petroleum producers and reducing (or increasing) this transfer has no effect on total global economic output or welfare. Because the United States is a net exporter, however, any change in petroleum spending by domestic consumers is offset by variation in revenues received by U.S. oil producers.⁷⁴⁸ NHTSA’s analysis focuses on U.S. domestic effects of changing CAFE standards, so the resulting change in the financial burden that oil purchases impose on the U.S. economy is important to acknowledge, even though it does *not* represent a real economic benefit or cost and is thus excluded from the agency’s regulatory analysis.

⁷⁴⁴ The figure shows 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 use feedstocks other than conventional petroleum, and technological innovations in petroleum extraction. The combination of these developments may 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 global supply curve will lie above the marginal cost curve because it will reflect market power of the colluding producers.

⁷⁴⁵ While U.S. demand influences prices, price is determined by the interaction of global demand and supply.

⁷⁴⁶ 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.

⁷⁴⁷ 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).

⁷⁴⁸ The decline in 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. NHTSA’s analysis of this action does not attempt to estimate the net effect of these changes in domestic consumer and producer surplus. If monopolistic 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 importantly, 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 Organization of the Petroleum Exporting Countries (OPEC) and Russia to engage in monopolistic behavior, NHTSA cannot estimate the magnitude of this cost or the reduction that would result from saving fuel.

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.⁷⁴⁹ Higher petroleum consumption exposes the United States to increased risks of rapid changes in oil prices triggered by global instability, and the same events that cause prices to change quickly can also disrupt supplies of imported oil. Because U.S. consumers of petroleum products are unlikely to take this increased risk into account when deciding how much gasoline or other petroleum products to consume, the “expected” costs of adapting to rapid price increases or enduring sustained supply disruptions represents an external cost of domestic petroleum consumption, and by changing gasoline consumption, setting CAFE standards can affect its magnitude.

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 any resulting reduction in U.S. economic output depends on the “oil intensity” of the domestic economy, as well as on 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 reduced at least *temporarily* 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 or impose costs they cannot fully recover even after normal market conditions return.

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. NHTSA constructs estimates of the economic 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. Reducing the probabilistic “expected value” of such costs by curtailing domestic fuel consumption and petroleum demand represents an external benefit of adopting or raising standards, and, conversely, any increase in their expected value resulting from increased petroleum demand represents an external cost of making standards less stringent.

⁷⁴⁹ See Bohi, D. R., & Montgomery, W. D. Oil Prices, Energy Security, and Import Policy, Johns Hopkins University Press: Washington, D.C. (1982), available at: <https://doi.org/10.4324/9781315673370> (accessed: May 22, 2026); Bohi, D. R., & Toman, M. A., Energy and Security: Externalities and Policies, *Energy Policy*, Vol. 21: pp. 1093 – 109 (1993), available at: <https://ideas.repec.org/a/eee/enepol/v21y1993i11p1093-1109.html> (accessed: May 22, 2026); Toman, M. A., The Economics of Energy Security: Theory, Evidence, Policy, in A. V. Kneese & J. L. Sweeney, eds., *Handbook of Natural Resource and Energy Economics*, Vol. III: Amsterdam - North-Holland, pp. 1167 – 218 (1993), available at: <https://ideas.repec.org/h/eee/natchp/3-25.html> (accessed: May 22, 2026).

6.2.4.3. Potential Effects of Fuel Consumption on U.S. Military Spending

A third potential effect of reducing U.S. demand for petroleum might be to enable the United States to reduce military spending for the purpose of securing the supply of oil imports from unstable regions of the world and protecting against their possible interruption. If military spending were clearly attributable to protecting flows of imported oil and could be scaled up or down as U.S. imports or consumption vary, the resulting changes in spending could represent an external benefit or cost of setting or changing CAFE standards. This is not the case, however, as the recent shift in the Nation’s position from a large importer to a net exporter of petroleum has not been accompanied by any significant reduction in military spending. U.S. military commitments in oil-producing regions of the world contribute primarily to worldwide economic and political stability, and insofar as the costs of these commitments are attributable to petroleum use, they are attributable to global oil consumption rather than to domestic consumption or U.S. imports alone. Consequently, the agency’s evaluation of these finalized standards assumes that government spending to support U.S. military activities will not vary in response to the anticipated increase in U.S. petroleum consumption.

6.2.4.4. Emerging Energy Security Considerations

As discussed above, energy security traditionally has referred to the Nation’s ability to acquire *petroleum* reliably and in sufficient quantities to meet domestic demand (for gasoline, in particular), and to do so at an acceptable cost. However, as the number of hybrid vehicles on the road continues to increase, the concept of energy security has expanded to encompass the United States ability to supply the materials necessary to build these vehicles. Currently, the most commonly used vehicle battery chemistries include materials that are either relatively scarce or expensive, are sourced from overseas sites,⁷⁵⁰ and (as with all mined minerals) can pose environmental challenges during extraction and conversion to usable material. These features of the battery material supply chain, including battery chemistry and sourcing origins, are changing rapidly. NHTSA does not include costs or benefits related to these emerging energy security considerations—or the analogous energy security considerations inherent in ICE vehicle supply chains—in its analysis for this final rule. The channels through which disruptions to these supplies impact domestic GDP have been shown to be less direct than in the case of oil petroleum. While this remains a potential concern for hybrid manufacturers, the scale of the problem is significantly lower for these vehicles than for BEVs due to the size and mineral composition of batteries typically used in each. For PHEVs mineral production disruptions could also generate a threat to supply chains, however these vehicles represent a relatively small share of the fleet in NHTSA’s analysis. NHTSA’s analysis is limited to the gas-powered fleet, and does not include BEVs, which removes the most significant source of these costs from the analysis.⁷⁵¹

6.2.4.5. Gasoline Consumption and Petroleum Imports

Though 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 also would depend

⁷⁵⁰ Barlock, T.A. *et al.*, Securing Critical Materials for the U.S. Electric Vehicle Industry: A Landscape Assessment of Domestic and International Supply Chains for Five Key Battery Materials, ANL-24/06, Final Report, ANL: Washington, D.C. (2024), available at: <https://publications.anl.gov/anlpubs/2024/03/187907.pdf> (accessed: May 22, 2026).

⁷⁵¹ See Knittel, C. *et al.*, The Differential Impacts of Critical Mineral Prices and Oil Prices on the Economy, NBER Working Paper w34847, (2026), available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=6246344 (accessed: May 22, 2026). The authors find that oil price increases are more contractionary for output and welfare than mineral price increases, which generate larger adjustments in investment, capital, and external borrowing.

partly on the fraction of U.S. petroleum use that is supplied by imports rather than by domestic production. Thus, 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 would be supplied by refining imported oil.

NHTSA estimates these costs separately for domestic and imported oil and then applies their values to its estimates of changes in the volume of fuel consumed that is reflected in changes in the volume of imported petroleum products and products refined domestically from imported crude petroleum.

Using the simplified model of the global oil market represented in Figure 6-6 above, the share of a reduction in domestic consumption that would be reflected in a decline in domestic refining is equal to the U.S. share of global 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:⁷⁵²

Equation 6-6: Calculation of Change in U.S. Domestic Gasoline Refining Relative to Consumption

$$\frac{\Delta U.S. \text{ Refining}}{\Delta U.S. \text{ Consumption}} = \frac{\eta_{US}^R R_{US}}{\eta_W^R R_W}$$

In Equation 6-6, R_{US}/R_W is the share of the world supply of refined petroleum products accounted for by the United States, while η_{US}^R and η_W^R are the price elasticities of U.S. and global supply of refined products. NHTSA decided that while both U.S. and global supply are likely to be more price-elastic in the long-run than in the near-term, even in the long-run supply is still likely upward-sloping, meaning that it increases at least slightly in response to increasing prices. NHTSA surveyed published literature but was unable to identify suitable estimates of the long-run price elasticities of U.S. and global supply of refined fuels, so for this final rule, the agency assumes these elasticities would be equal. The relative price sensitivities of refiners in the United States and the rest of the world are determined by their relative refining costs as well as regional demand, both of which are difficult to project over the timeframe of NHTSA's analysis, and because the ratio of these elasticities could change in either direction over the long term, NHTSA believes its assumption that they are equal represents a reasonable approach. Based on the share of U.S. refined product production, NHTSA then assumes that 80 percent of any reduction in fuel consumption is accounted for by lower imports of foreign fuel, and 20 percent is accounted for by reductions in domestic refining.

In turn, the agency believes that changes in domestic gasoline consumption and refining are 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 changing 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.

As one indication of the likely minimal impacts of higher U.S. gasoline consumption on U.S. production of crude petroleum, NHTSA examined differences between EIA's AEO 2026 Counterfactual Baseline

⁷⁵² 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 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.

Case and its Alternative Transportation and Electricity Case. The Counterfactual Baseline Case includes all policies in place in fall 2025, including EPA’s vehicle tailpipe emission standards for MYs 2027+, and EPA’s low NO_x requirements for freight trucks. The Alternative Transportation and Electricity case excludes these policies, and comparing these two cases shows that the large difference in U.S. gasoline consumption between them is accompanied by a much smaller difference in U.S. crude petroleum production for exactly the reasons described above. By 2050, domestic petroleum product consumption projected in the absence of those standards is about 17-percent higher than in Counterfactual Baseline case, while U.S. crude petroleum production differs by only about 1 percent between the two scenarios.

Considering the factors that influence U.S. petroleum supply and comparing EIA’s projections of future changes in U.S. petroleum production under very different levels of domestic gasoline consumption, NHTSA believes that in the context of the current global petroleum market, changes in U.S. gasoline demand on the scale likely to result from adopting any of the alternative standards considered for this final rule are unlikely to cause significant changes in domestic petroleum production or fuel refining. Instead, they seem more likely to affect the distribution of crude petroleum and gasoline produced within the United States between domestic consumption and U.S. exports to global markets, rather than by affecting domestic petroleum production. Thus, the agency continues to assume that 90 percent of any change in domestic refining will lead to changes in U.S. exports of crude petroleum, while only the remaining 10 percent of that change would be reflected in variation in domestic petroleum production.⁷⁵³

6.2.4.6. Estimates of Energy Security Benefits Used to Evaluate the Final Rule

For this final rule, NHTSA is using a methodology consistent with its approach from the NPRM to update its estimates of energy security externalities. The agency is continuing to produce its own estimates of these externalities using methods described in Brown (2018).⁷⁵⁴ For this final rule, NHTSA updated these estimates to reflect changes in projections of oil market conditions between the 2025 AEO and the more recent 2026 AEO. The advantage of basing NHTSA’s estimates on a clear, well-established methodology is that these estimates can be presented transparently and can also be 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, allowing NHTSA to examine the robustness of its analysis of the effect of changes to CAFE standards.

NHTSA limits its quantification of oil market externalities to the effect of oil supply shocks on expected GDP losses that may result from temporarily elevated prices (caused by the short-term inelasticity of oil supply and demand).⁷⁵⁵ As indicated in previous sections, the agency does not consider changes in the value of transfers between petroleum consumers and producers resulting from the effects of variation in

⁷⁵³ 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®ion=0-0&cases=ref2023&start=2021&end=2050&f=A&sourcekey=0> (accessed: May 22, 2026).

⁷⁵⁴ See Brown, S., New Estimates of the Security Costs of U.S. Oil Consumption, *Energy Policy*, Vol. 113: pp. 171 – 92 (2018), available at: <https://doi.org/10.1016/j.enpol.2017.11.003> (accessed: May 22, 2026).

⁷⁵⁵ As indicated in the previous subchapter, if large petroleum suppliers are able to exercise market power and sustain global prices above competitive levels, there may be 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, NHTSA’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.

U.S. gasoline demand on global oil prices as economic costs or benefits of changing CAFE standards, and is skeptical of claims that changes in U.S. petroleum imports would permit (or require) corresponding changes in military spending and thus create additional costs or benefits from adjusting standards.

Sudden or unexpected increases in prices for petroleum products disrupt economic growth and have, in the past, been followed by economic slowdowns. Reducing domestic petroleum consumption can affect 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 rapid changes in oil prices 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 to the United States will decline, thus reducing the expected size of any global supply disruptions and mitigating their potential 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 will decline, amplifying 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 changes in oil imports and in 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 via imports. Both estimates capture the marginal effect of a one-barrel change in petroleum consumption and are scaled down to a per-gallon basis for use in the agency's CAFE Model, where each gallon of variation in domestic petroleum consumption resulting from a change in CAFE standards either averts or adds to the estimated total costs of energy security.

Following Brown, NHTSA defines the effect of a petroleum supply shock of magnitude D_i on U.S. GDP, Y_{US} , when the initial 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 Q_W is global supply prior to the shock D_i and η is a composite short-run elasticity of global oil prices with respect to changes in global supply, defined as:

$$\eta = (\eta_{DUS} + \eta_{YUS} \eta_{GUS}) \frac{Q_{DUS}}{Q_W} + (\eta_{DROW} + \eta_{YROW} \eta_{GROW}) \frac{Q_{DROW}}{Q_W} - \eta_{SUS} \frac{Q_{SUS}}{Q_W} - \eta_{SROW} \frac{Q_{SROW}}{Q_W}$$

Here NHTSA defines 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, and QD_{US} is the quantity of U.S. oil consumption. Similarly, 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, and QD_{ROW} is the quantity of foreign oil consumption. Finally, 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 NHTSA's 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)⁷⁵⁶ and is 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:

$$E(\Delta Y) = \sum_{i=0}^n \phi_i \cdot \Delta Y_i(D_i)$$

Here, the changes in GDP from normal oil market conditions during a shock of magnitude D_i are weighted by the probability ϕ_i that such a shock occurs, and those individual probability-weighted GDP changes are summed over the distribution of possible supply shocks to arrive at their expected value.

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 recalculates a perturbed value, $E(\Delta Y'_i)$.⁷⁵⁷ 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:

$$\Delta E(\Delta Y) = \sum_{i=0}^n \phi_i \cdot (\Delta Y'_i(D_i) - \Delta Y_i(D_i))$$

NHTSA projects its estimates using oil market and macroeconomic conditions from the 2025 AEO Alternative Transportation Case. This approach is consistent with NHTSA's approach in the 2024 final rule. NHTSA uses a range of elasticity estimates taken from Brown (2018), including more recent estimates and older estimates. This reflects NHTSA's desire to use the full range of evidence in developing its estimates, given uncertainty over how the U.S. economy will respond to future oil price shocks. While NHTSA only uses its mean estimates in its central analysis, the agency does consider the full range of its estimates in the sensitivity analysis.

Table 6-17 reports the estimates of reduced per-barrel external costs from potential oil price shocks that this analysis uses to estimate the change in the total value of those external costs likely to result from tightening or resetting CAFE standards. The change in their total value is estimated by multiplying the number of gallons by which petroleum consumption is projected to change as a consequence of a new

⁷⁵⁶ Beccue, P. and Huntington, H., An Updated Assessment of Oil Market Disruption Risks: Final Report, Energy Modeling Forum, Stanford University: Stanford, CA. pp. 1-75 (2016), available at: https://mpira.ub.uni-muenchen.de/74986/1/MPRA_paper_74986.pdf (accessed: May 22, 2026).

⁷⁵⁷ 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.

CAFE standard by this estimated per-gallon premium.⁷⁵⁸ These estimates are calculated using the detailed procedure described above and expressed per barrel by which changing standards would increase or reduce U.S. petroleum consumption.

Table 6-18: Expected Cost of Petroleum Price Shocks

Year	Oil Security Premium (2024\$/Barrel) ⁷⁵⁹	AEO 2026 Alternative Transportation and Electricity Case West Texas Intermediate Crude Oil Spot Price (2024\$/Barrel)
2025	4.60	63.19
2026	4.70	48.39
2027	4.73	53.81
2028	4.79	58.04
2029	4.89	61.69
2030	4.99	62.65
2031	5.07	65.57
2032	5.15	65.79
2033	5.24	67.72
2034	5.32	68.31
2035	5.40	69.60
2036	5.46	70.90
2037	5.53	72.55
2038	5.59	74.07
2039	5.64	74.91
2040	5.69	75.35
2041	5.73	76.22
2042	5.76	77.55
2043	5.79	79.05
2044	5.83	80.11
2045	5.86	81.91
2046	5.89	83.22
2047	5.90	84.12
2048	5.93	85.91

⁷⁵⁸ This calculation assumes that reduced petroleum consumption by drivers of the regulated fleet would reduce the estimated external costs in proportion to their consumption.

⁷⁵⁹ In order to convert per-barrel costs into per-gallon costs, NHTSA makes the common assumption (used throughout the analysis) that each barrel of petroleum produces 42 gallons of motor gasoline.

2049	5.96	87.97
2050	5.98	88.55

Because these estimates are based on separate estimates of the effect of changes in consumption on U.S. oil imports and domestic petroleum production, they require the agency to project changes in U.S. petroleum imports that are likely to result from changes in fuel consumed resulting from setting CAFE standards. Changes in domestic petroleum supply represent the difference between changes in domestic consumption and U.S. imports. As discussed in Chapter 6.2.4.5, DOT has elected to assume that changes in U.S. petroleum consumption caused by raising or lowering fuel economy standards will have only a limited impact on domestic oil production. Thus, 90 percent of any decrease in domestic refined fuel production attributable to CAFE standards would be reflected in lower crude oil imports.

6.2.5. Changes in Labor Utilization

Changes in vehicle prices resulting from regulatory costs of fuel economy standards affect new vehicle sales, which in turn affect automotive employment. In addition, production of newer technologies associated with fuel economy regulation will impact 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 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 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 LDV unit sales; (2) assembly labor for vehicles, engines, and transmissions related to new vehicle unit sales; and (3) labor related to incremental fuel-saving 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.⁷⁶⁰ The analysis estimates labor effects from the forecasted CAFE Model technology costs and from a review of automotive labor for the MY 2024 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 49 U.S.C. part 583 (AALA) submissions for each vehicle in the reference fleet. The analysis assumes the portion of parts that are made in the United States remain constant for each vehicle as manufacturers add technologies as a result of fuel economy regulation. This should not be misconstrued as a prediction that the percentage of U.S. made parts—and by extension U.S.

⁷⁶⁰ NHTSA recognizes a few local production facilities may contribute meaningfully to local economies, but the analysis reports only on national effects.

labor—will remain constant, but rather that NHTSA 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 new vehicles. The CAFE Model estimates sales in response to the different regulatory alternatives by considering changes in new vehicle prices and new vehicle fuel economy levels.⁷⁶¹ As vehicle prices rise and fuel consumption falls, NHTSA expects vehicle sales to be affected. For this analysis, NHTSA assumes that if manufacturers sell more vehicles, they will require more labor to produce those vehicles and dealers will need more labor to sell those vehicles. However, as manufacturers alter the portfolio of technologies added to each new vehicle, the industry demand for labor resources to develop, sell, and produce additional fuel economy technologies will decrease.⁷⁶² NHTSA also accounts for the possibility that fuel economy 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. NHTSA accounts for the anticipated changes in vehicle sales, shifts in the mix of passenger cars and light trucks, and the addition of fuel-saving technologies that result from the regulation.

For this analysis, NHTSA assumes that some factors affecting labor utilization will remain fixed at MY 2024 levels in future years. While innovation is likely to lead to further efficiency gain in output per worker, for simplicity NHTSA assumes that assembly labor hours per unit will remain at estimated MY 2024 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, NHTSA assumes that revenue per employee from suppliers and OEMs will also remain constant, even as manufacturers add 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. NHTSA does not consider how direct labor changes may affect the macro economy and potentially change employment in adjacent industries. For instance, NHTSA does not consider possible labor changes in vehicle maintenance and repair, nor does it consider changes in labor at retail gas stations. NHTSA also does not consider possible labor changes due to raw material production, such as production of aluminum, steel, and copper, nor does NHTSA consider possible labor impacts due to changes in production of oil and gas, or ethanol.

Finally, NHTSA makes no assumptions regarding part-time-levels 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. Schmalensee and Stavins

⁷⁶¹ See Chapter 4.2.1.

⁷⁶² For the purposes of this analysis, NHTSA assumes a linear relationship between labor and production volumes.

show 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 in the long run.⁷⁶³ 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, NHTSA does not include multiplier effects in the main CAFE Model analysis but instead focuses 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 NADA annual report,⁷⁶⁴ and AALA reports, which are available on the NHTSA website.⁷⁶⁵ The NADA report includes information regarding dealership employment related to new LDV 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 LDV 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,⁷⁶⁶ as their effect from 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.

NHTSA calculates 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. NHTSA uses 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).⁷⁶⁷ Using these values, NHTSA estimates

⁷⁶³ Schmalensee, R., & Stavins, R., A Guide to Economic and Policy Analysis of EPA’s Transport Rule, White Paper, EPA-HQ-OAR-2010-0799-0676 (2011), available at: https://obamawhitehouse.archives.gov/sites/default/files/omb/assets/oira_2060/2060_06132011-1.pdf (accessed: May 22, 2026).

⁷⁶⁴ Manzi, P., National Automotive Dealers Association, Annual Financial Profile of America’s Franchised New-Car Dealerships, NADA: Tysons, VA (2021), available at: <https://www.nada.org/media/4695/download?inline> (accessed: May 22, 2026) (hereinafter, “NADA Data 2021”).

⁷⁶⁵ Part 583 American Automobile Labeling Act Reports, last revised: 2023, available at: <https://www.nhtsa.gov/part-583-american-automobile-labeling-act-reports> (accessed: May 22, 2026).

⁷⁶⁶ 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.

⁷⁶⁷ NADA Data 2021.

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 6-7 shows how the final labor hours per-vehicle value is calculated.

Equation 6-7: Calculation of Labor Hours per New Vehicle Sold

$$\text{labor hours per new vehicle sold} = \frac{\text{annual labor hours} * \text{new vehicle sales jobs}}{\text{new vehicles sold}}$$

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

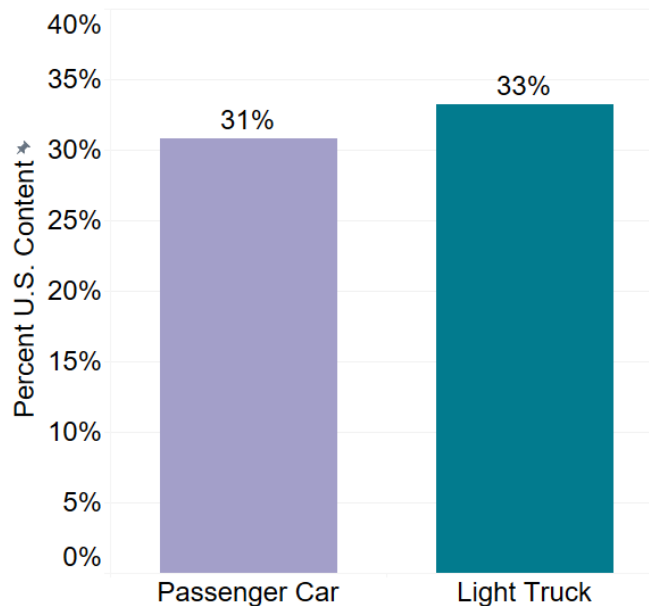
New vehicles sold = total number of new vehicles sold in dealerships

NHTSA estimates that on average, dealership employees working on new vehicle sales labor for 24.64 hours per new vehicle sold. This estimate of labor hours per new vehicle 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 manufacturer. As part of this analysis, NHTSA identifies specific assembly locations for final vehicle assembly, engine assembly, and transmission assembly for each MY 2024 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 6-7 shows the average percent of U.S. (and Canadian) content, weighted by sales, of passenger cars and light trucks in MY 2024, post vehicle reclassification.

Figure 6-7: Sales-Weighted Percent U.S. Parts Content by Light-Duty Regulatory Class (MY 2024)⁷⁶⁸



NHTSA estimates average direct assembly labor per vehicle (30 hours), per engine (4 hours), and per transmission (5 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.⁷⁶⁹ These reports are grouped at the vehicle trim level, with a few exceptions that report variations in percent content within the trim level.

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 0 hours if the manufacturer imports the vehicle, engine, and transmission. Equation 6-8 shows the how NHTSA calculates the U.S. assembly employment hours associated with each vehicle in the Market Data Input File.

Equation 6-8: Calculation of U.S. Assembly Employment Hours

$$\begin{aligned}
 &U.S. \text{ Assembly Employment hours} \\
 &= (Vehicle \text{ Assembly location} * 30) + (Engine \text{ Assembly location} * 4) \\
 &+ (Transmission \text{ Assembly location} * 5)
 \end{aligned}$$

Where:

Vehicle assembly location = Portion of U.S. content, 1 = fully U.S.

⁷⁶⁸ Vehicle reclassification changes the percentage of domestic labor displayed in the chart when the light-duty fleet is subdivided, but given vehicle classification is not anticipated to influence where vehicles are produced, the total labor hours across all vehicle classifications remains constant throughout the analysis.

⁷⁶⁹ Part 583 American Automobile Labeling Act Reports, last revised: 2023, available at: <https://www.nhtsa.gov/part-583-american-automobile-labeling-act-reports> (accessed: May 22, 2026).

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. NHTSA surveyed motor vehicle and equipment manufacturing labor statistics from the U.S. Census Bureau, BLS, and other publicly available sources. NHTSA 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 2001-2013 at a ratio of 5.26.⁷⁷⁰ 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, NHTSA scales 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 are scaled up or down as unit sales are scaled up or down over time in the CAFE Model.

6.2.5.2.3. *Fuel Economy Technology Labor*

In instances in which manufacturers spend additional dollars on fuel economy technologies as a result of CAFE standards, 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, NHTSA makes a simplifying assumption that revenue per labor hour at OEMs and suppliers will remain about the same as in MY 2024 even as manufacturers include additional technology. To estimate the average revenue per labor hour at OEMs and suppliers, the analysis looks 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 and 2024, covering more than 40 publicly traded suppliers, and NHTSA estimates that OEMs will add one labor year per each \$760,690 increment in revenue and that suppliers will add one labor year per \$357,638 in revenue.⁷⁷¹

NHTSA applies these global estimates to all revenues, and the share of U.S. content is applied as a later adjustment.⁷⁷² 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 regulated vehicles to ensure that they are domestic for the MDPCS.

The additional labor hours associated with added fuel economy technology are calculated by the CAFE Model based on the values seen in Equation 6-9 and reported as part of the total labor hour outputs (see the Vehicles Report).

Equation 6-9: Calculation for Fuel Economy Technology Labor Hours

Fuel economy tech labor hours

⁷⁷⁰ North American Industry Classification System Code 3361, 3363.

⁷⁷¹ 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.

⁷⁷² U.S. content information is found in the AALA reports discussed in Chapter 6.2.5.1.

$$= \left(\frac{\text{Vehicle tech cost}}{\text{OEM revenue}} + \frac{\frac{\text{Vehicle tech cost}}{\text{Supplier revenue}}}{\text{RPE}} \right) * \text{Percent U.S. content} * \text{Annual labor hours}$$

Where:

Fuel economy tech labor hours = labor hours spent on additional fuel economy 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 added 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, simulated 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. NHTSA set the value of this parameter at 1.00 (see the Parameters Input File). Equation 6-10, Equation 6-11 and Equation 6-12 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 6-10: 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 6-11: Calculation of Innovation Hours per Vehicle

$$\text{Innovation hours} = \left(\frac{\text{Vehicle tech cost}}{\text{OEM revenue}} + \frac{\frac{\text{Vehicle tech cost}}{\text{Supplier revenue}}}{\text{RPE}} \right) * \text{Percent U.S. content} * \text{Annual labor hours}$$

Equation 6-12: 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 final rulemaking analysis.

7. Safety Impacts of Regulatory Alternatives

Fuel economy standards affect vehicle safety in several ways. Historically, one approach manufacturers used to comply with fuel economy standards was to build smaller and lighter vehicles. While the transition to attribute-based fuel economy standards has somewhat diminished the primacy of mass-reduction as a means to improve efficiency as a compliance strategy, reduction of a vehicle’s mass remains a highly effective approach to meeting standards. And when two vehicles of different masses collide, the change in velocity is greater in the vehicle with less mass. All other factors being equal, the risk of fatality or injury is greater in the vehicle with less mass. In cases where fuel economy improvements were achieved through reductions in vehicle size and mass—especially with smaller and lighter vehicles—safety risks can be attributable to increased standards stringency.

NHTSA uses attribute-based standards to reduce the incentive to downsize vehicles to comply with standards. The agency considers the possibility of safety-related trade-offs when developing fuel economy standards. In particular, the analysis includes the examination of safety impacts from three factors:

1. **Changes in Vehicle Mass.** NHTSA analyzes whether there are any safety impacts from changes in vehicle mass made in response to the standards. Statistical analyses of historical crash data indicate that reducing mass in heavier vehicles generally improves safety in the overall fleet (but not for occupants in those vehicles), while reducing mass in lighter vehicles generally reduces safety (for both the overall fleet and for occupants of those vehicles).
2. **Impacts of Vehicle Prices on Fleet Turnover.** Newer vehicles are safer due to increasingly stringent safety regulations and continuous voluntary safety improvements driven by innovation. The agency expects this trend to continue as emerging technologies—such as advanced driving assistance systems (ADAS) and engineering improvements that continually enhance occupant protection—are incorporated into new vehicles. Safety improvements are expected to continue regardless of changes to the CAFE standards, but the pace with which these improvements penetrate the on-road fleet is affected by CAFE standards. As discussed in Final TSD Chapter 4.2, technologies are added to comply with increases in fuel economy standards and result in increases in vehicle prices. Increased vehicle prices slow 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 LD fleet. As the safety provided by light trucks, SUVs, and passenger cars responds differently to technology that manufacturers employ to meet the standards—particularly mass reduction—fleets with different compositions of body styles have varying numbers of fatalities. Therefore, changing the share of each type of LDV in the projected future fleet affects 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.

These three factors generate differences in safety outcomes among regulatory alternatives. The agency’s analysis allocates the differences in safety outcomes among these three factors. Fatalities, injuries, and property damage-only (PDO) crashes are projected by deriving a fleetwide fatality rate (fatalities per-vehicle-miles traveled). The fleetwide fatality rate incorporates the effects of differences in each of the

three factors from baseline conditions and multiplying that rate 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 external to VSL measurements. Traffic injuries and property damage are also modeled directly using the same process and valued using costs specific to each injury severity level.

Only two of the factors—changes in vehicle mass and changes in the LD fleet composition—directly impose increased risks on drivers and passengers. In contrast, increased driving associated with the rebound effect is a consumer choice that reveals the benefit of additional travel. For consumers who choose to drive more, the utility of additional driving exceeds the additional costs—even despite the perceived crash risk 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 LDV safety: fatalities to vehicle occupants and non-occupants (pedestrians, cyclists, and others) from crashes, serious injuries sustained by occupants and non-occupants, and the number of vehicles involved in crashes that cause property damage without injuries. Counts of fatalities to vehicle occupants and non-occupants involved in crashes are obtained from NHTSA's Fatal Accident Reporting System (FARS). Estimates of the number of serious injuries to occupants of LDVs and non-occupants involved in crashes 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 are 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 are 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 detailed in FRIA Chapter 5.

7.1. Projecting Future Fatalities and the Safety Baseline

To estimate the safety effect of alternative standards, the agency uses 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 model tracks model year cohorts of vehicles as they are produced, sold, and enter the fleet. Each model tracks model year cohorts as they age and accumulate usage (*i.e.*, change ownership), and as they retire from service. NHTSA considers how introducing newer technologies is 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 LDV fleet during any future calendar year is determined by: the safety performance of the individual model year cohorts comprising it, the ages they reach in a given calendar 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 (*e.g.*, 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 forecast 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 LD fleet.

7.1.1. Historical Trends

The relationships between 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 to 6 years old, after accounting for the vehicle's model year and various factors related to the severity of the crash.⁷⁷³ The increase in risk is more pronounced for the oldest vehicles in use. Occupants of vehicles 15 years or older are 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).

Rates of fatalities and serious injuries suffered by LDV occupants and other road users involved in crashes (mainly pedestrians and cyclists) have declined gradually for several decades into the 2010s. Despite the recent divergence from this long-run trend during the early 2020s, fatalities and serious injuries returned to their gradual declines in 2022 through 2024. 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 (ESC), sophisticated crash avoidance systems, and improvements in occupant protection performance. NHTSA's 2020 study showed that occupants of cars and light trucks produced in MYs 1995-2011 are 15 percent more likely to sustain serious injuries in crashes than occupants of vehicles from more recent model years (MYs 2012-2018). Occupants of pre-1987 cars and light trucks are 50 percent more likely to be seriously injured in crashes than occupants of vehicles from more 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. Over time, the safety performance of each new model year cohort differs from its predecessors as successive model years entering the fleet have generally become safer due to improvements in their design, increased durability resulting from changes in materials and manufacturing methods, safety regulations, and voluntary adoption of safety-improving features. The safety performance of each individual model year cohort evolves as it ages, accumulates use, and the remaining vehicles in use are acquired by new owners. The "age-period-cohort" approach disaggregates the evolution of fleetwide 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 and affect the safety of all model years in the fleet.

⁷⁷³ Liu, C. & Subramanian, R., The Relationship Between Passenger Vehicle Occupant Injury Outcomes and Vehicle Age or Model Year in Police-Reported Crashes, Traffic Safety Facts Research Note, Report No. DOT HS 812 937, NHTSA: Washington, D.C. (2020), available at: <https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812937> (accessed: May 20, 2026).

The safety performance of individual model year cohorts tends to follow a common pattern as they age, accumulate use, and experience changes in ownership and locations where they are driven.^{774,775}

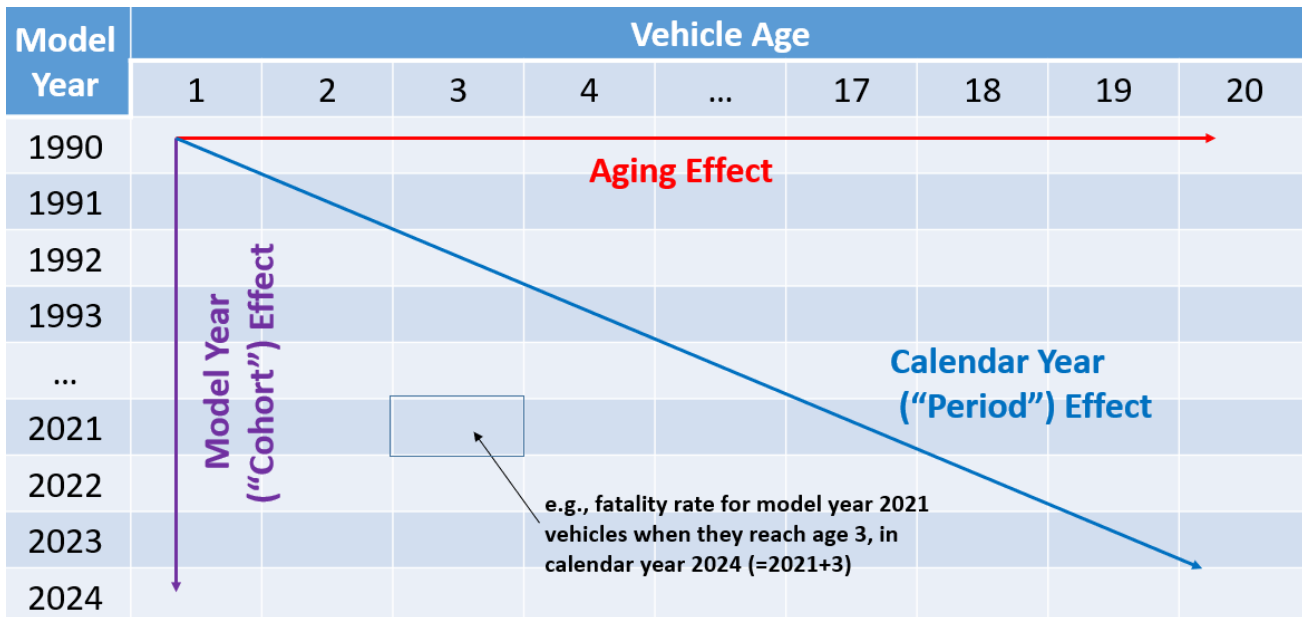
Historically, vehicle safety appears to deteriorate gradually through approximately up to age 20. It then levels off for some period, and in rare cases, safety may improve thereafter. The causes of this pattern are not completely understood. The agency suspects the major factors contributing to the decline in safety through age 20 are: vehicle purchase and use by habitually riskier drivers, shifts toward areas where road conditions are less safe, and travel speeds are higher.

Figure 7-1 illustrates the age-period-cohort framework as applied to the safety of vehicle travel. New model years have generally become progressively safer, and these improvements tend to persist throughout their lifetimes in the fleet, which represents a cohort effect. Vehicles are gradually involved in more frequent and dangerous accidents as they age and accumulate use. 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 (*i.e.*, 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 gradually 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.

⁷⁷⁴ 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-saving 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.

⁷⁷⁵ U.S. content information is found in the AALA reports discussed in Chapter 6.2.5.1. Eun, S., 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. 105325 (2020), available at: <https://doi.org/10.1016/j.aap.2019.105325> (accessed: May 20, 2026); Langley, J. *et al.*, Age, Period and Cohort Effects on the Incidence of Motorcyclist Casualties in Traffic Crashes, *Injury Prevention*, Vol. 19(3): pp. 153 – 57 (2013), available at: <https://doi.org/10.1136/injuryprev-2012-040345> (accessed: May 20, 2026).

Figure 7-1: Age, Cohort, and Period Effects on Safety of Vehicle Fleet



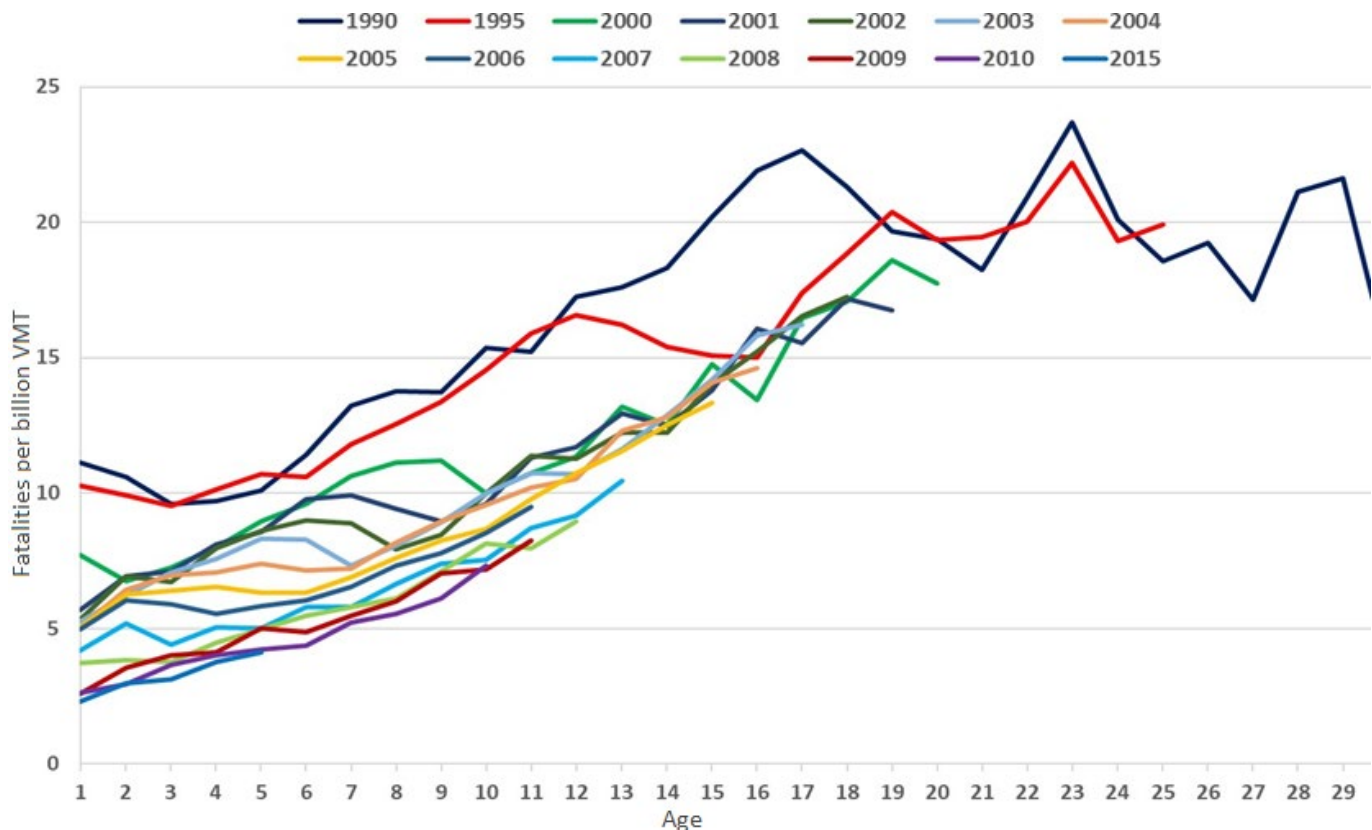
7.1.3. The Aging Effect

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.⁷⁷⁶ 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, though structural fatigue with increased usage and resulting mechanical failures play a small role in the increase.⁷⁷⁷ 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.

⁷⁷⁶ 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 FARS, available at: <https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars>. Fatalities among non-vehicle occupants occurring in crashes involving vehicles of different model years were prorated 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 minus model year and dividing the count of fatalities for each model year and age by the number of miles vehicles 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 PDO crashes were tabulated from NHTSA’s National Automotive Sampling System General Estimates System NASS GES), available at: <https://www.nhtsa.gov/national-automotive-sampling-system/nass-general-estimates-system>, 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 that involved vehicles of different model years were assigned on the basis of those to vehicle occupants. Non-fatal injury and PDO crash rates show patterns of variation over historical model years and age that are similar to those for fatalities shown in Figure 7-2.

⁷⁷⁷ National Center for Statistics and Analysis, How Vehicle Age and Model Year Relate to Driver Injury Severity in Fatal Crashes, Traffic Safety Facts Research Note, Report No. DOT HS 811 825, NHTSA: Washington, D.C. (2013), available at: <https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/811825> (accessed: May 20, 2026).

Figure 7-2: Fatality Rates by Age for Selected Model Years



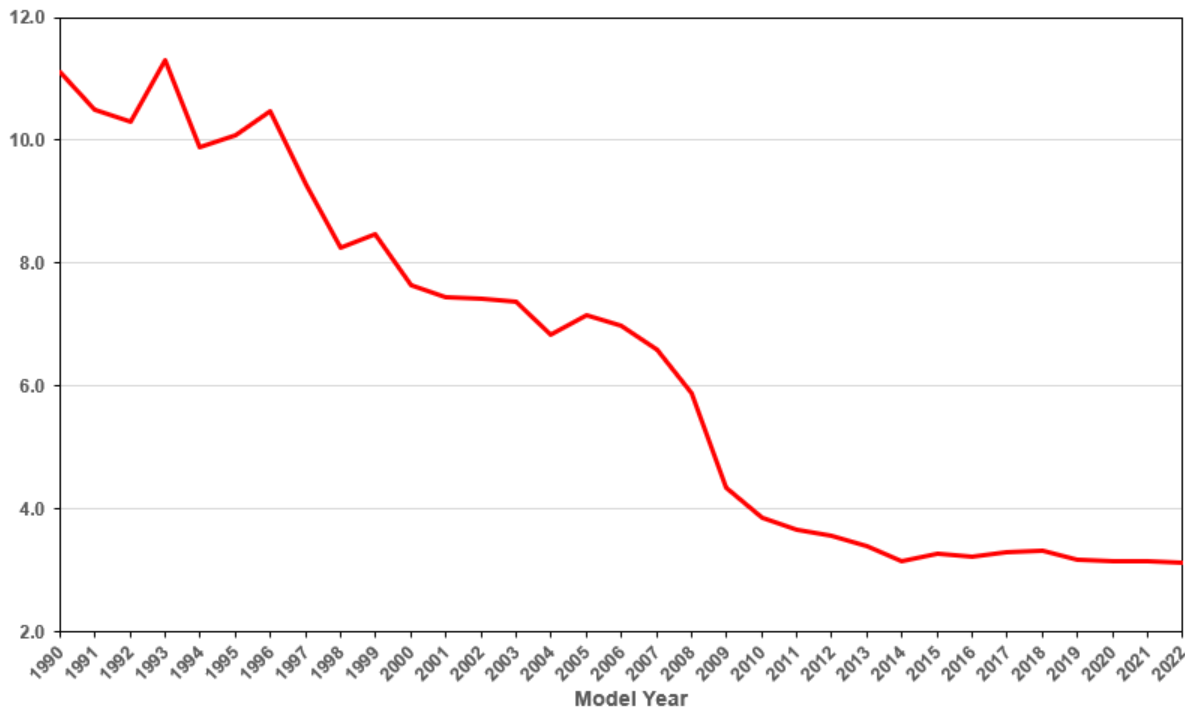
7.1.4. Safer New Cars: The Cohort Effect

Figure 7-3 isolates the fatality rates for recent model years during the first years after each one is produced, sold, and registered initially for use.⁷⁷⁸ It illustrates the gradual decline in new vehicles' fatality rates over successive model years, but it also shows that this decline has proceeded in distinct steps rather than continuously. As the figure suggests, some of the largest improvements in new LDV safety coincide with the implementation of NHTSA safety regulations. These safety regulations include those requiring front-seat air bags (2000), side air bags (2006–2008), and TPMS (2008).

To reflect the historical pattern of safety improvements shown in Figure 7-3, NHTSA groups successive model years with similar fatality rates into a smaller number of cohorts when new. This is based on visual examination of the figure and the effective dates of NHTSA safety regulations. Grouping model years this way enables more reliable identification of the effect of vehicle age, because 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.

⁷⁷⁸ Vehicles from each successive new model year are produced and sold over a period spanning well over a single calendar year, so NHTSA uses their average fatality rate for the first 2 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

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, though 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 women and older drivers. 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. Road conditions in the latter tend to be safer with lower travel speeds, which reduces the frequency and severity of crashes.

Other important period influences on safety include driver behavior. Factors such as 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 of alcohol has, generally, trended slightly downward over the years and reduced crash incidence, drug-impaired and distracted driving are increasingly common factors contributing to motor vehicle crashes. 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 responses to crash situations by emergency vehicles and personnel, together with improved effectiveness of emergency medical treatment, appear to have reduced the consequences of injuries to occupants of vehicles involved in crashes.

7.1.6. Measuring Safety

The agency has developed separate statistical models to project future rates of fatalities, non-fatal injuries, and PDO crashes per billion vehicle-miles of travel. Fatality rates are 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 is used to calculate rates of non-fatal injuries and vehicles sustaining property damage per involved vehicle per billion vehicle-miles. Fatalities are tabulated using NHTSA's FARS, while non-fatal injuries and vehicles sustaining property damage are estimated from NHTSA's GES and CRSS crash sampling systems using appropriate expansion weights for each crash type.

As discussed in detail in Final TSD Chapter 4.3, the number of vehicle-miles driven is estimated by multiplying the number of vehicles originally produced during each model year that are projected to remain in use in a subsequent calendar year by the average number of miles that vehicles of their age are driven annually.⁷⁷⁹ This produces fatality rates by calendar year and model year for each calendar year from CYs 1990–2022; the model years included range from MY 1975 (the earliest for which reliable registration data were available) to MY 2023 (the newest model year in the fleet during CY 2022). A similar process is used to calculate non-fatal injuries to LDV occupants as well as non-occupants involved in crashes per billion miles driven, and the number of cars and light trucks involved in PDO crashes per billion miles driven.

Defining a model year's age as the number of calendar years since its introduction (age equals calendar year minus 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. 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 reflects period-specific influences 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 disentangle fully the aging and period effects on any single model year's safety.⁷⁸⁰ NHTSA employs groups of model years with similar safety records during their initial year of use to address this problem, though this technique does not overcome this conceptual challenge fully.

NHTSA uses model years from MYs 1975–2022 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 employs fixed effects to represent model years.⁷⁸¹ Because the data used to develop the Model are 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. Older model years are observed only during the later years of their service

⁷⁷⁹ 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 MY 2000 were age 10 during CY 2010, because 2010–2000 = 10.

⁷⁸⁰ Viewed another way, defining age = calendar year – model year means that there can be independent variation in only two of the three variables (because the two variables uniquely determine the third), so it is impossible to identify their three separate effects on safety.

⁷⁸¹ For an introduction to this method, see Wooldridge, J. M., *Introductory Econometrics: A Modern Approach*, 4th ed, South-Western Cengage Learning, at Chapters 13 and 14, (2009).

lives, while the most recent model years are observed only at the very early ages of their expected lifetimes.⁷⁸²

For example, the earliest model year included in CY 1990, the first year of the estimation period, is MY 1977, which had already reached age 14 by then. The newest model year observed in CY 2019 is MY 2019, defined to be of age=1.⁷⁸³ The data used to derive these models end in 2022 due to the time lag in reporting the crash and injury records included in NHTSA’s FARS and CRSS, so any impact of the COVID-19 on long-term trends is excluded from this analysis. However, the agency feels that many of the changes to driving patterns during the pandemic represent an aberration to the underlying secular trends in vehicle crashes, and hence their exclusion likely enhances the precision of capturing long-term trends that will prevail over the coming decades.

7.1.7. Model Specification and Estimation

NHTSA groups successive model years with similar fatality or injury rates during their first year in use into “safety cohorts” and constrains the fixed effects for the model years making up each cohort to be identical. This approach provides some variation in the age of vehicles making up each cohort during any calendar year, which improves the ability of the statistical models to measure the independent effects of age and period variables. NHTSA groups 30 model-year vintages and assigns them to 10 safety cohorts based on the calendar year in which they are new in the fatality rate model. Some cohorts correspond to only a single model year while others include as many as eight consecutive model years. NHTSA uses the same grouping of model years into cohorts for the non-fatal-injury and property-damage crash models.

As Figure 7-2 suggests, age plays an important role in explaining the safety performance of model year cohorts over their lifetimes, though its effect appears complex; each cohort’s fatality rate increases linearly to about age 15, but then levels off and appears to decline for those model years that reached ages greater than 20. To capture this pattern, all the model specifications NHTSA tested use both age and its squared value as explanatory variables, and some include the cubed value of age in an effort to reproduce the pattern shown in Figure 7-2.

⁷⁸² Though 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- to 15-year “expected” lifetimes of light-duty vehicles, or the length of time that a typical car or light truck remains in use after it is produced and initially sold.

⁷⁸³ 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 non-occupants killed or injured in crashes involving them) and property damage they sustain are included with those of the current model year. For example, some MY 2023 cars and light trucks were in use during CY 2022, and consequences of crashes in which they were involved during that year were included with those for MY 2022.

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			
% 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 are obvious candidates for explanatory variables are closely correlated over the historical period NHTSA analyzed (CYs 1990–2022). This makes it nearly impossible to identify their independent effects. To address this difficulty, NHTSA substitutes 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. NHTSA experiments with more complex specifications to test whether the rate of improvement in fleetwide safety has been constant over time. This includes using a non-linear time trend and testing for more abrupt changes in the rate of improvement in safety during the analysis period.⁷⁸⁴ NHTSA finds 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 analyzed period. However, neither the simple linear nor the more complex time trends fully capture the effects on safety associated with the economic recessions in 1991, 2001–2002, and 2008–2011. NHTSA supplemented the time trend with indicator (or “dummy”) variables to capture temporary departures from the longer-term trend during those years. Safety appears to improve consistently during these recession periods compared to the predicted levels using the time trend alone.

With minor variations, NHTSA uses the same model specification to analyze trends in non-fatal injuries per billion miles driven by cars and light trucks and in the number of vehicles involved in crashes that resulted in property-damage per billion miles. The data are used to estimate these models and span the shorter period from CYs 1990–2022. During this period, NHTSA implemented a new crash sampling system and overcame difficulties in using two systems to generate continuous and consistent data series. The groupings of model years into safety cohorts used in these models differ slightly from the fatality rate model.

⁷⁸⁴ 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.

7.1.8. Fatality Rate Model

Table 7-2 summarizes estimation results for preferred specifications of the fatality rate, non-fatal injury rate, and PDO crash models. The fatality rate model uses the natural logarithm of fatalities per billion miles driven as its dependent variable. The model specification includes: fixed effects for model year groups (*i.e.*, 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. Interactions between model year groups and age are included as a test of whether the effect of age on fatality rates has changed for more recent model years. Overall, the specification reported in Table 7-2 replicates 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.

After MYs 1996-1997, the estimated fixed effects for model year groups decline consistently over more recent model years, reflecting consistent reductions in fatality rates associated with new vehicles with successive transitions from one model year “cohort” to the next.⁷⁸⁵ The positive value of the fixed effect for MYs 1996-1997 indicates that fatality rates for new vehicles produced during those model years *increased* compared to MYs 1990-1995. The fatality rates for MYs 1990-1995 (when new) are reflected in the model’s constant term and may reflect the rapid shift in sales of new vehicles from passenger cars toward LD trucks. This shift generally exhibits higher fatality rates than passenger cars during the mid-1990s. The values of the diagnostic statistic rho reported as the second to last line in Table 7-2, 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 fleetwide safety.

Extensive testing confirms the difficulty of identifying the separate effects of individual period effect variables on fatality rates.⁷⁸⁶ When used alone in the model, the unemployment rate and use of lap and shoulder belts each appear to reduce fatality rates significantly. However, their effects are muted when combined. Driving under the influence of alcohol is strongly associated with higher fatality rates, but any combination of those three variables in the model vastly reduces the precision of their estimated effects. It can even change their apparent direction. Increased use of hand-held electronic devices appears to *reduce* fatality rates when it is added to the Model. This result strongly contradicts expectations and could be a possible artifact related to the difficulty of measuring its growth accurately. Alternatively, it could be an artifact of its correlation with trends in improving technology in vehicles. Positive coefficient estimates for the fraction young male licensed drivers and the fraction of rural area travel suggests that declines over time in both measures contribute significantly to the decline in fatality rates. Using either one in conjunction with other time-varying measures causes pronounced changes in their estimated coefficients. For example, sometimes changes in their arithmetic signs make all 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. Doing this avoids the need to obtain reliable forecasts of factors measured by the period variables, such as unemployment, use of seat

⁷⁸⁵ 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 NHTSA 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.

⁷⁸⁶ 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.

belts and smartphones, and driving under the influence of alcohol. These all have complex underlying causes that make their future patterns difficult to project. Of course, extrapolating a time trend into the future assumes that the factors that trend represents continue to change and affect safety in the same ways those factors have in the recent past. Thus, the preferred specification reported in Table 7-2 employs a time trend. 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. 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.

Coefficient estimates for the time trend variable and its square consistently indicate that some combination of the period effects is intended to capture reduced fatality rates early in the estimation period. However, the sign and magnitude of the estimated coefficient for the square of the trend variable suggests that the initial decline in fatality rates has slowed substantially throughout the estimation period.

The chosen model allows 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, though Figure 7-1 above suggests that any such change does not appear to be pronounced. The form of this interaction is quite restrictive. It implies that the effects of age (and its squared value, where included) change by equal increments with each successive model year cohort. However, the coefficient estimates for those models suggest the increase in fatality rates through vehicles' early ages has become slightly less steep for more recent model years. Nevertheless, these fatality trends are consistent, and thus NHTSA projects lifetime vehicle fatality rates using the chosen model onto recent and future model years. These projections form the fatality estimates for the reference baseline alternative.

Specifically, NHTSA employs the coefficient estimates for the fatality rate model reported in Table 7-2 to forecast reference baseline fatality rates for model years making up the future fleet. NHTSA elects to use this specification because it possesses many features NHTSA considers important for understanding the effects of vehicle aging on safety. The Model accounts for historical variation in fatality rates (including a time trend whose "steepness" declines throughout the estimation period and age effects that become less pronounced for more recent model years). The Model's estimated parameters are plausible in both magnitude and sign direction. The fixed effects parameters for model year groups exhibit declining magnitude as vehicle vintages become newer. Finally, the Model fits the data as well or better than any of the alternative specifications NHTSA 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.

Table 7-2: Estimation Results for Fatality Rate, Non-fatal Injury Rate, and Property-Damage-Only Models

Explanatory Variables	Outcomes		
	Fatality Rate	Non-fatal Injury Rate	Property-Damage-Only Crashes
Constant (MYs 1990-1995)	2.017***	7.012***	7.853***
	(0.045)	(0.124)	(0.054)
MYs 1996-1997	0.0569	0.246**	0.178***
	(0.035)	(0.098)	(0.043)
	-0.128**	0.156	0.204***

MYs 1998-2002	(0.052)	(0.144)	(0.063)
MYs 2003-2005	-0.235***	0.14	0.220***
	(0.064)	(0.176)	(0.077)
MY 2006	-0.307***	0.254	0.295***
	(0.079)	(0.220)	(0.095)
MY 2007	-0.372***	0.413*	0.334***
	(0.086)	(0.238)	(0.103)
MYs 2008-2009	-0.444***	0.401*	0.366***
	(0.086)	(0.238)	(0.103)
MY 2010	-0.568***	0.256	0.342***
	(0.097)	(0.270)	(0.117)
MYs 2011-2017	-0.705***	0.33	0.299***
	(0.086)	(0.238)	(0.103)
MYs 2018-2022	-0.837***	0.148	0.117
	(0.120)	(0.332)	(0.144)
ln Age	0.154***	0.156***	0.113***
	(0.009)	(0.025)	(0.011)
ln Age2	-0.00666***	-0.00852***	-0.00583***
	(0.000)	(0.001)	(0.001)
ln Age3	5.63e-05***	9.34e-05***	5.45e-05***
	(0.000)	(0.000)	(0.000)
ln Time	-0.0154***	-0.0955***	-0.0452***
	(0.005)	(0.014)	(0.006)
ln Time2	0.000518***	0.00230***	0.00133***
	(0.000)	(0.000)	(0.000)
1991	-0.232***	-0.241*	-0.0622
	(0.047)	(0.129)	(0.056)
2009	-0.193***	-0.145*	-0.113***
	(0.028)	(0.078)	(0.034)
2010	-0.121***	-0.0232	-0.0352
	(0.028)	(0.077)	(0.033)
MY Group x Age	-0.0172***	-0.0195***	-0.0130***
	(0.002)	(0.005)	(0.002)
MY Group x Age ²	0.00103***	0.00113***	0.000658***
	(0.000)	(0.000)	(0.000)
Observations	891	891	891
R2	0.891	0.509	0.791
R2 within	0.739	0.459	0.727
R2 between	0.990	0.640	0.344
sigma_u	0.293	0.128	0.115

sigma_e	0.159	0.440	0.191
rho	0.773	0.078	0.267
Corr(ui,xb)	0.529	-0.038	0.175

7.1.9. Non-Fatal Injury Rates

Table 7-2 reports estimation results for a similar model that explains historical variation in non-fatal injuries to occupants of LDVs and non-occupants involved in crashes. As with the fatality rate model, the dependent variable 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 varies among both model years of different ages during any calendar year, and for each model year over the span of calendar years when it is represented in the data sample.

The specification reported in Table 7-2 groups model years from MYs 1990-2022, 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 model for non-fatal injury rates employs the time trend variables discussed previously to help capture the combined effects of several time-varying or period influences on safety, which are too closely correlated with one another to enable their separate effects to be identified reliably.

The coefficient estimates for model year groups are reported in Table 7-2 and reveal the same initial increase in injury rates for MYs 1996-1997 as was evident for fatality rates. The constant term represents the fatality rate for the earliest model years to appear as new vehicles in the estimating sample, MYs 1990-1995. The coefficient estimates do not show the same systematic decline for more recent model years as was evident with fatality rates. It is possible that this pattern 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. Examining injury trends for individual severity categories suggests this may be the case. Partly as a consequence of the limited explanatory power of fixed effects for the model year cohorts, the model for injury rates does not explain observed variation as well as did those for fatality rates, as shown by the R-squared measure reported in Table 7-2. 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 CY 1990. However, allowing the trend to “flatten” over time by including its squared value again suggests rapid slowing of that initial decline. 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 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 their predecessors’ injury rates did.

The agency ensures consistency with its forecasts of fatality rates by developing forecasts of baseline injury rates. The baseline injury rates are used to analyze the safety consequences of slowing sales of new cars and trucks and increased retention of older-model-year vehicles. NHTSA uses the coefficient estimates for the preferred specification as shown in Table 7-2. As with fatality rates, this specification has the advantages of including all variables that contribute significantly to explaining variation in fatality rates. The estimated effects of fatality rates align with expectations in directions and magnitude and fit the data as well as any alternative specification NHTSA tested.

7.1.10. Property Damage Rates

Table 7-2 reports the results of estimating the preferred model specification for crashes that involve only damage to vehicles or immediately surrounding property. Counts of vehicles sustaining property damage

are obtained from NHTSA's GES and CRSS crash sampling systems. The counts are 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 7-2, the dependent variable of each model is the natural logarithm of the number of vehicles involved in PDO crashes per billion vehicle-miles driven by cars and light trucks, and this measure 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 the preferred specification indicate that this model generally does a better job of explaining those two sources of variation than was the case for injury rates, though it still does not perform quite as well as the model for fatality rates.

The preferred specification of the property damage equations groups 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 MYs 1996-1997 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 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 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 7-2 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 7-2 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.

Choosing the 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 used its preferred specification shown in Table 7-2 to develop forecasts of property damage rates for the future LD 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.

7.1.11. Using the Models to Forecast

To simplify forecasting future rates for fatalities, non-fatal injuries, and involvement in PDO crashes in the baseline, NHTSA utilizes 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. NHTSA uses the coefficient estimates reported for the three different outcomes in Table 7-2.

The process begins by estimating fatality, injury, and property damage crash involvement rates for new cars and light trucks that are produced in future model years. Starting with the relevant rate for the latest model year included in the estimation data when it was new (for example, the fatality rate for MY 2022 during CY 2022), NHTSA applies 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

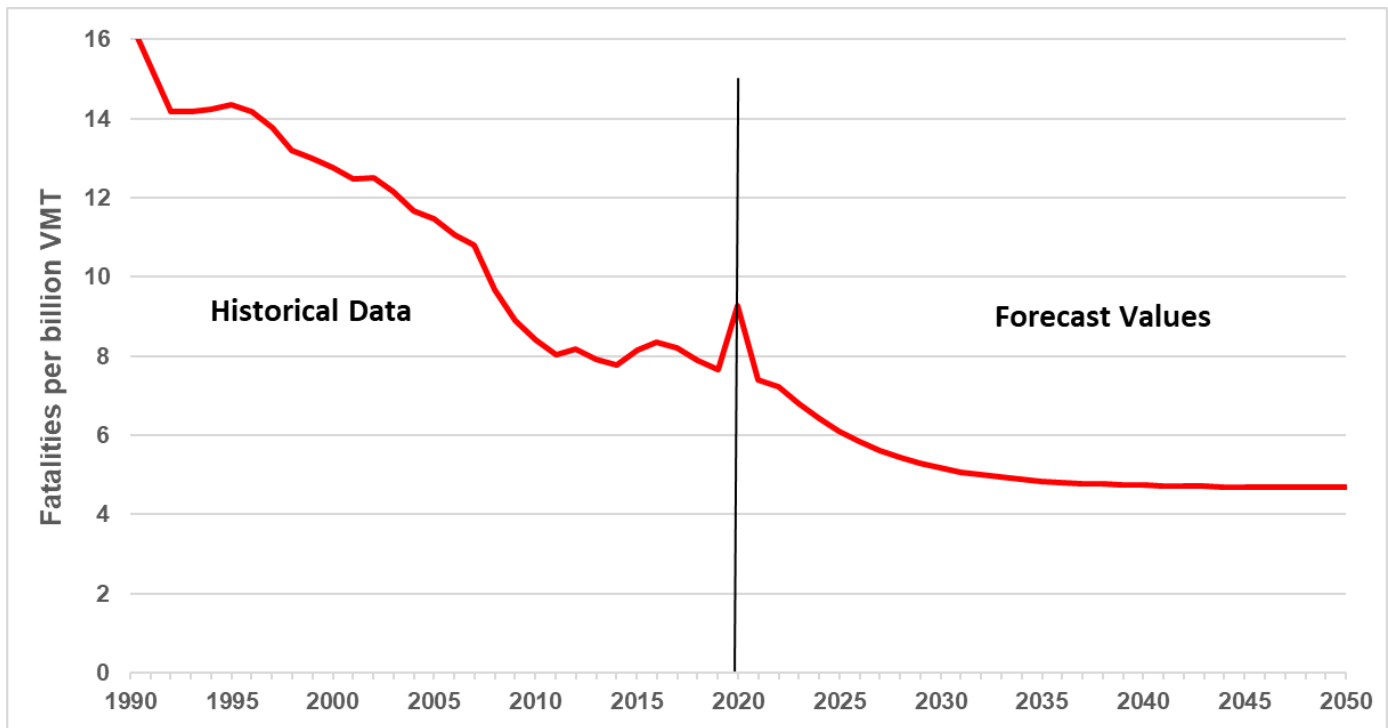
of each technology in reducing specific crash “modes” (e.g., rollover or head-on), and the contribution of each crash mode to fatalities, injuries, or property damage. The following subchapter discusses the nature of these technologies, projects the shares of new vehicles that will be equipped with each 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 a vehicle’s 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 rates of fatalities, injuries, and property damage per billion miles during its first year in use. At the same time, the rates for each earlier model year in the fleet are increased to reflect the effect of having aged an additional year, as calculated from the coefficients on the age-related variables in the relevant historical model. 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 fatality, non-fatal injury, or property damage rates 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 control both model year cohort effects and age.

This method 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 CY 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 PDO 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 and accompanying restrictions on activity, and an increase in fatalities that is not yet fully explained but may be due to riskier driving on less congested roadways. These rates are 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 and accompanying restrictions on activity as well as a rise in fatalities.⁷⁸⁷

7.2. Future Safety Trends Predicted by Advanced Safety Technologies

The model as described so far uses trends observed over several decades to make estimated projections of future safety rates. To augment these projections with knowledge about forthcoming safety improvements, the agency applies detailed empirical estimates of the market uptake and the improving effectiveness of crash avoidance technologies to estimate their effect on the fleetwide fatality rate. This process includes 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 not equipped with these technologies and the safety of other road users such as pedestrians and cyclists.

The development of advanced crash avoidance technologies in recent years indicates some level of certainty that safety improvement will 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 or certainty regarding autonomous vehicles’ eventual deployment and impact to include them in this analysis.

Advanced technologies currently deployed or in development include:

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

⁷⁸⁷ NHTSA, 2020 Fatality Data Show Increased Traffic Fatalities During Pandemic, last revised: June 3, 2021, available at: <https://www.nhtsa.gov/press-releases/2020-fatality-data-show-increased-traffic-fatalities-during-pandemic> (accessed: May 21, 2026).

detection capability, such as Radio Detection and Ranging (RADAR), Light Detection and Ranging (LIDAR) (laser), or video cameras, 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.

Automatic Emergency Braking (AEB) systems actively apply brakes when a crash is determined to be imminent, to avoid or mitigate the impact of rear-end collisions. These systems include Crash Imminent Braking (CIB) and Dynamic Brake Support (DBS). 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, and video cameras. 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). 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 (*e.g.*, RADAR, LIDAR, or video cameras) 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. Though the implementation of DBS 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.

Pedestrian Automatic Emergency Braking (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.

Rear Automatic Braking features sense the presence of objects behind a reversing vehicle, alert the driver of the presence of objects via auditory and visual alerts, and automatically engage the available braking system(s) to stop the vehicle.

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.

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.

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.

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.

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), which are expected to drive future safety improvements, to estimate the impacts of crash avoidance technologies. NHTSA analyzed seven crash avoidance technologies currently being produced and commercially deployed in the new vehicle fleet: FCW, AEB, LDW, LKA, BSD, LCA, and PAEB. These are the principal technologies being developed and adopted in new vehicle fleets and will likely drive vehicle-based safety improvements for the coming decade. Manufacturers are installing more of these ADAS technologies over time. 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 seven technologies address four basic crash scenarios through warnings to the driver or, alternately, through dynamic vehicle control:

Forward collisions, typically involving a crash into the rear of a stopped vehicle;

Lane departure crashes, typically involving inadvertent drifting across or into another traffic lane;

Blind spot crashes, typically involving intentional lane changes into unseen vehicles driving in or approaching the driver's blind spot; and

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 are attributable to improved protection when a crash occurs (crashworthiness), 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 measures these impacts by deriving effectiveness rates for these advanced crash avoidance technologies from the safety technology literature. NHTSA then applies these effectiveness rates to specific crash target populations that the crash avoidance technology is designed to mitigate, adjusted to reflect the current pace of adoption of the technology, including the public commitment by manufacturers to install these technologies. The products of these factors, combined across all seven 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 finalized standards can be examined.

7.2.2. Technology Effectiveness Rates at Reducing Fatalities

To focus the agency’s attention on more recent studies (conducted after 2017) to reflect more current safety systems and vehicle designs, for this analysis, NHTSA based its projections for all technologies except PAEB on Leslie *et al.* (2019)⁷⁸⁸ because the report contains confidence bounds applicable for lower and upper bound sensitivity analysis cases. Subsequent iterations of this University of Michigan Transportation Research Institute (UMTRI) report omit this information and provide only point estimates of coefficient values. Apart from PAEB, the estimated effectiveness of advanced crashed avoidance technologies does not change substantially in subsequent reports. Furthermore, the annual reports produced by Leslie *et al.* since 2019 are the only studies to report estimates for each of the six crash avoidance technologies analyzed for the final rule, which provides a level of consistency across 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. Recent effectiveness estimates for ADAS technologies from the empirical literature are presented in Table 7-3.

Table 7-3: Summary of ADAS Technology Effectiveness Literature Estimates

Study	Tech	Crashes	Fatalities	Injuries	Notes
Cicchino (2017) ⁷⁸⁹	FCW	27%		20%	
	Low AEB	43%		45%	
	High AEB	50%		56%	
	BSD	14%		23%	
Sternlund, Strandroth <i>et al.</i> (2017) ⁷⁹⁰	LDW/LKA			6–30%	
Yanagisawa <i>et al.</i> (2017), NHTSA Report No. DOT HS 812 400. ⁷⁹¹	PAEB		91%-96.5%**		**Low speed, daylight, head on crashes only.
Cicchino (2018) ⁷⁹²	LDW	11%		21%	

⁷⁸⁸ Leslie, A. *et al.*, Analysis of the Field Effectiveness of General Motors Production Active Safety and Advanced headlighting Systems, UMTRI-2019-6, University of Michigan Transportation Research Institute: Ann Arbor, MI (2019), available at: <https://deepblue.lib.umich.edu/bitstream/handle/2027.42/150660/UMTRI-2019-6%20FINAL%20.pdf> (accessed: May 21, 2026).

⁷⁸⁹ Cicchino, J. B., 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 (2017), available at: <https://doi.org/10.1016/j.aap.2016.11.009> (accessed: May 21, 2026).

⁷⁹⁰ Sternlund, S. *et al.*, The Effectiveness of Lane Departure Warning Systems – A Reduction in Real-World Passenger Car Injury Crashes, *Traffic Injury Prevention*, Vol. 18(2): pp. 225 – 29 (2017), available at: <https://doi.org/10.1080/15389588.2016.1230672> (accessed: May 21, 2026).

⁷⁹¹ Yanagisawa, M. *et al.*, Estimation of Potential Safety Benefits for Pedestrian Crash Avoidance/Mitigation Systems, Report No. DOT HS 812 400, NHTSA: Washington, D.C. (2017), available at: <https://rosap.ntl.bts.gov/view/dot/12475> (accessed: May 21, 2026).

⁷⁹² Cicchino, J. B., Effects of Lane Departure Warning on Police-Reported Crash Rates, *Journal of Safety Research*, Vol. 66: pp. 61 – 70 (2018), available at: <https://doi.org/10.1016/j.jsr.2018.05.006> (accessed: May 21, 2026).

Isaksson-Hellman & Lindman (2018) ⁷⁹³	LCA	30%		31%**	** Crashes with repair costs greater than \$1,250.
Leslie <i>et al.</i> (2019) ⁷⁹⁴	FCW	21%			
	AEB	46%			
	LDW	10%			
	LKA	20%			
	BSD	3%*			* Not statistically significant.
	LCA	26%			
Spicer <i>et al.</i> (2021) ⁷⁹⁵	AEB	43%			
	PAEB	16%			
	LKA	4–9%			
	LDW	4%			
	BSD	4%			
Leslie <i>et al.</i> (2021) ⁷⁹⁶	FCW	20%			
	AEB	45%			
	PAEB	14%*			* Not statistically significant.
	LDW	10–12%			
	LKA	9–16%			
Insurance Institute for Highway Safety (IIHS)/Cicchino (2022) ⁷⁹⁷	PAEB	25–27%	29–30%	3%*	* Not statistically significant.
Leslie <i>et al.</i> (2022) ⁷⁹⁸	FCW	20%		25%	
	AEB	40–45%		55–58%	
	PAEB	23%			
	LDW	4–8%			
	LKA	8–17%			
	LCA	16%			

⁷⁹³ Isaksson-Hellman, I. & Lindman, M., 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): pp. S104 – 11 (2018), available at: <https://doi.org/10.1080/15389588.2017.1396320> (accessed: May 21, 2026).

⁷⁹⁴ Leslie, A. *et al.*, Analysis of the Field Effectiveness of General Motors Production Active Safety and Advanced Headlighting systems, UMTRI-2019-6, University of Michigan Transportation Research Institute: Ann Arbor, MI (2019), available at: <https://hdl.handle.net/2027.42/150660> (accessed: Apr. 14, 2026).

⁷⁹⁵ Spicer, R. *et al.*, Effectiveness of Advanced Driver Assistance Systems in Preventing System-Relevant Crashes, SAE Technical Paper 2021-01-0869, SAE International: Warrendale, PA (2021), available at: <https://www.sae.org/publications/technical-papers/content/2021-01-0869/> (accessed: May. 21, 2026).

⁷⁹⁶ Leslie, A. *et al.*, Field Effectiveness of General Motors Advanced Driver Assistance and Headlighting Systems, *Accident Analysis & Prevention*, Vol.159: p. 106275 (2021), ISSN 0001-457575, available at: <https://doi.org/10.1016/j.aap.2021.106275> (accessed: May 21, 2026).

⁷⁹⁷ Cicchino, J. B., Effects of Automatic Emergency Braking Systems Pedestrian Crash Risk, *Accident Analysis & Prevention*, Vol. 172: p. 106686 (2022), available at: <https://doi.org/10.1016/j.aap.2022.106686> (accessed: May 21, 2026).

⁷⁹⁸ Leslie, A. *et al.*, Analysis of the Field Effectiveness of General Motors Model Year 2013-2020 Advanced Driver Assistance System Features, UMTRI-2022-2, University of Michigan Transportation Research Institute: Ann Arbor, MI (2022), available at: <https://deepblue.lib.umich.edu/bitstream/handle/2027.42/171916/UMTRI-2022-2.pdf> (accessed: May 21, 2026).

	BSD	8%			* Not statistically significant.
PARTS Summary Report DRAFT (2022)	PAEB		4%*	2%*	* Not statistically significant.
Leslie <i>et al.</i> (2023) ⁷⁹⁹	FCW	14%		25%	
	AEB	40–49%		53–57%	
	PAEB	23%			
	LDW	(-5) –9%*			* Not statistically significant.
	LKA	7–15%			
	LCA	15			
	BSD	-4%*			* Not statistically significant.
Leslie <i>et al.</i> (2024) ⁸⁰⁰	FCW	16%		28%	
	AEB	40–49%		51–52%	
	PAEB	31%			
	LDW	(-8) –14%*			* Not statistically significant.
	LKA	8–16%			
	LCA	12%			
	BSD	-7%*			* Not statistically significant.
Leslie <i>et al.</i> (2025) ⁸⁰¹	AEB	39–54%		28%	
	PAEB			25%	
	LDW	(-30) – (-13)%*			* Not statistically significant.
	LKA	(-1) –8%*			* Not statistically significant.
	BSD	11%			

7.2.2.1. Forward Crash Collision Technologies

Cicchino (2017) analyzes the effectiveness of a variety of forward collision mitigation systems, including both FCW and AEB systems. The analysis is based on crashes occurring during 2010–2014 in 22 States and controls for other factors that affect crash risk. Cicchino finds that FCW reduced all rear-end striking crashes by 27 percent and rear-end striking injury crashes by 20 percent, and that, when functional at high speeds, AEB reduced these crashes by 50 and 56 percent, respectively. Cicchino also finds that low-speed AEB without driver warning reduces all crashes by 43 percent and injury crashes by 45 percent. Furthermore, Cicchino found a significant, 30-percent reduction in rear-end injury crashes, even in crashes on roadways where speed limits exceed 50 mph.

Spicer *et al.* (2021) focus on ADAS technology effectiveness in 2.3 million Toyota vehicle crashes linked to 308,490 police-reported crashes from 2015–2018. The authors found that AEB in Toyota vehicles led to a statistically significant reduction of 43 percent in front-to-rear crashes.

Research from UMTRI is updated annually using a rolling window of model year GM vehicles. The results from these studies are relatively consistent for AEB and FCW systems and correspond with the

⁷⁹⁹ *Id.*

⁸⁰⁰ *Id.*

⁸⁰¹ *Id.*

values used in the CAFE safety analysis. Leslie *et al.* (2019) analyze the relative crash performance of 123,377 GM MYs 2013-2017 vehicles linked to State police-reported crashes by VIN. GM provides VIN-linked safety content information for these vehicles to enable precise identification of safety technology content. The authors analyze the effectiveness of a variety of crash avoidance technologies, including both FCW and AEB separately. They estimate 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.* (2019) find that FCW reduces rear-end striking crashes of all severities by 21 percent, and that AEB (which includes FCW) reduces these crashes by 46 percent.⁸⁰²

Leslie *et al.* (2021) expand their previous analyses of relative crash performance to GM MYs 2013-2019. The authors estimate the effectiveness of FCW, AEB, and PAEB using the linked data. They find that FCW reduces rear-end struck crashes by 20 percent, radar-based AEB reduces rear-end struck crashes by 45 percent, and camera-based AEB reduces such crashes by 38 percent. Leslie *et al.* (2022) find that FCW reduces rear-end struck crashes by 20 percent, radar-based AEB reduces rear-end struck crashes by 45 percent, and camera-based AEB reduces such crashes by 40 percent for GM MYs 2013-2020. Leslie *et al.* (2023) find that, for MYs 2017-2021, radar-based AEB reduces crashes by 49 percent, camera-based AEB reduces crashes by 40 percent, and FCW's reported effectiveness is 14 percent, which is lower than in the above analyses incorporating earlier model years. Leslie *et al.* (2024) find comparable crash reduction numbers for AEB systems and finds that FCW reduces rear-end struck crashes by 16 percent for vehicles in MYs 2018-2022. Leslie *et al.* (2025) find similar results to prior years for MYs 2019-2023 with radar-based AEB systems reducing rear-end struck crashes by 54 percent, camera-based AEB systems reducing reported crashes by 39 percent, and FCW reducing crashes by 17 percent. The weighted effectiveness of the two AEB technologies for MYs 2019-2023 is approximately 40.2 percent.

Leslie *et al.* (2019) measure effectiveness against all categories of crashes but do 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. The agency's 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.* (2019) find effectiveness rates of 21 percent for FCW and 46 percent for AEB. NHTSA's central fatality effectiveness estimates were determined to 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. The agency's 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.

⁸⁰² NHTSA notes that UMTRI, the sponsoring organization for the Leslie *et al.* study, published a previous version of this same study using the same methods in March 2018 (Flannagan, C., Leslie, A., Crash Avoidance Technology Evaluation Using Real-World crashes, Ann Arbor, MI: University of Michigan Transportation Research Institute, (2018). NHTSA 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.

7.2.2.2. Pedestrian Crash Avoidance Technologies

Yanagisawa, Swanson, Azeredo, and Najm (2017) use simulation studies to estimate the effectiveness of PAEB technologies. They focus 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 crash 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 to 2018. The authors do not find a statistically significant reduction in pedestrian crashes with PAEB. The point estimate is 16-percent reduction with a 95-percent confidence interval that ranges from a 31-percent reduction to a 4-percent increase in pedestrian crashes.

UMTRI's analysis by Leslie *et al.* (2021) expands on the authors' previous analyses of relative crash performance of GM MYs 2013-2019. The effectiveness of PAEB is statistically insignificant, and the point estimate of the effect on front pedestrian crash incidences is a 14-percent reduction. Leslie *et al.* (2022) find 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 users, the authors find that frontal pedestrian braking reduces the incidence rate of pedestrian crashes by 23 percent. This is due in part to many GM vehicles adopting PAEB technologies in MY 2020. UMTRI's analysis also found that IntelliBeam/automatic high beam headlights reduced vulnerable road user collisions by 22 percent during nighttime conditions.⁸⁰³ Leslie *et al.* (2023), Leslie *et al.* (2024), and Leslie *et al.* (2025) updated the analysis using a moving sample of model years and found roughly comparable results for PAEB.

The IIHS/Cicchino (2022) study focuses on the effectiveness of PAEB on crash incidence, crashes with injury, and crashes with severe injury or fatalities for MYs 2017-2020. They find comparable results to UMTRI's analysis. PAEB installation reduces pedestrian crashes by 25–29 percent, and crashes with pedestrian injury by 29 to 30 percent. While not statistically significant, the results suggest a 3- to 29-percent reduction in fatalities/severe injury. The study does not find clear evidence that PAEB reduces pedestrian fatalities due to low statistical power.

The values for PAEB effectiveness used in the CAFE Model for fatalities are derived from the values used in final PAEB/AEB Rulemaking (FRIA) in 2024. The effectiveness value for PAEB on fatalities used in the final rule is 39 percent. The estimate of 39 percent effectiveness is 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.⁸⁰⁴ The engineering-based assumptions are 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 is applied in this analysis because empirical studies have lacked the statistical power to clearly identify

⁸⁰³ 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 percent.

⁸⁰⁴ Pedestrian crashes are more likely to result in a fatality than other crash types, and this suggests that many pedestrian crashes that initially result in severe injury also eventually result in a fatality. As such, this analysis uses an effectiveness measure that incorporates information on crashes involving serious injury as most representative, yielding the 39-percent effectiveness value from the PAEB/AEB Rulemaking (FRIA). See NHTSA, Federal Motor Vehicle Safety Standards; Automatic Emergency Braking Systems for Light Vehicles, Docket No. NHTSA-2023-0021, available at: https://www.nhtsa.gov/sites/nhtsa.gov/files/2024-04/final-rule-automatic-emergency-braking-systems-light-vehicles_web-version.pdf (accessed: May 21, 2026); see AEB Test Devices, Final Regulatory Impact Analysis p. 290, Docket No. NHTSA-2023-0021-1069, available at: <https://www.regulations.gov/document/NHTSA-2023-0021-1069> (accessed: May 26, 2026).

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

Cicchino (2018) focuses on single-vehicle, sideswipe, and head-on crashes as the relevant target population for LDW effectiveness rates in 2009–2015 police-reported data from 25 States. The study is limited to crashes on roadways with 40 mph or greater speed limits and 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 finds an overall reduction in relevant crashes of 11 percent for vehicles that are equipped with LDW. She also finds a 21-percent reduction in injury crashes. The result for all crashes is not statistically significant, while that for injury crashes approaches significance ($p < 0.07$). Cicchino does not separately analyze LKA systems.

Sternlund *et al.* (2017) studies single-vehicle and head-on injury crash involvements relevant to LDW and LKA in Volvos on Swedish roadways. The crashes studied are limited to roadways with speeds of 70–120 kph and not covered with ice or snow. Sternlund *et al.* find that LDW/LKA systems reduce single-vehicle and head-on injury crashes in their crash population by 53 percent, with a lower limit of 11 percent, which they determine corresponds to a reduction of 30 percent (lower limit of 6 percent) across all speed limits and road surface assumptions.

Spicer *et al.* (2021) focuses on ADAS technology effectiveness in 2.3 million Toyota vehicle crashes linked to 308,490 police-reported crashes from 2015 to 2018. Generally, LDW and LKA in Toyota vehicles fail to result in statistically significant reductions in their targeted crashes. The only statistically significant crash reductions attributable to LKA were run-off roadway crashes, a point estimate of 9 percent with a 95-percent confidence interval of 1–16 percent.

Leslie *et al.* (2019) analyze the relative crash performance of 123,377 GM MYs 2013–2017 vehicles linked to State police-reported crashes by VIN. The authors analyzed the effectiveness of a variety of crash avoidance technologies, including both LDW and LKA separately. Leslie *et al.* find that LDW reduces lane departure crashes of all severities by 10 percent and that LKA (which includes LDW) reduces these crashes by 20 percent. Leslie *et al.* (2022) disaggregates the effects of LDW and LKA based on types of crashes, opposite direction, same direction, and off-road crash types. For crashes involving vehicles traveling in the same direction, LDW reduces incidents by four percent and LKA reduced incidents by 10 percent. There is 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 reduces crashes is 6.99 percent. For LKA the reduction is 14.76 percent. Leslie *et al.* (2023), Leslie *et al.* (2024), and Leslie *et al.* (2025) update the analysis using a moving sample of model years. In later model years, the effectiveness of LDW becomes statistically insignificant. The effectiveness for LKA is consistent across studies until Leslie *et al.* (2025).

As noted previously for frontal crash technologies, NHTSA bases its 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. NHTSA's central effectiveness estimates are thus 10 percent for LDW and 20 percent for LKA. For sensitivity analysis, NHTSA adopts 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

Cicchino (2017) examines 4,620 lane change crashes, including 568 injury crashes. Cicchino finds 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) focuses on ADAS technology effectiveness in 2.3 million Toyota vehicle crashes linked to 308,490 police-reported crashes from 2015 to 2018. 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.

In UMTRI’s analysis of GM vehicles, Leslie *et al.* (2019), find that BSD reduces lane departure crashes of all severities by 3 percent (non-significant) and that LCA (which includes BSD) reduces these crashes by 26 percent. Leslie *et al.* (2022) find that BSD technology reduces crash incidents by 8 percent (non-significant). For LCA inclusive of BSD, the authors find these technologies reduce only 16 percent of target crashes. Leslie *et al.* (2023), Leslie *et al.* (2024), and Leslie *et al.* (2025) update the analysis using a moving sample of model years and find roughly comparable results for LCA. BSD’s effectiveness becomes negative and statistically insignificant as new model years are examined.

Isaksson-Hellman and Lindman (2018) find that Volvo’s Blind Spot Information System (does not significantly reduce the overall number of lane change crashes of all severities, but they do find a significant 31-percent reduction in crashes with a repair cost exceeding \$1,250, 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. The agency’s central effectiveness estimates are thus 3 percent for BSD and 26 percent for LCA. For sensitivity analysis, NHTSA adopts the 95-percent confidence intervals from Leslie *et al.* For LCA, this range is 16.59-33.74 percent. For BSD, the upper range is 14.72 percent, but the findings are not statistically significant. The agency therefore is limiting the range to 0-14.72 percent.

Table 7-4 summarizes the effectiveness rates established in the literature and the rates NHTSA used to analyze each technology’s impact on fatalities in the safety analysis.

Table 7-4: 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 <i>et al.</i> 2017/UMTRI September 2019 Report								
^b PAEB AEB Rulemaking RIA (2024)								

7.2.3. Technology Effectiveness Rates at Reducing Non-fatal and Property Damage-Only Crashes

The same data and methods used 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 rates 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. NHTSA assumes effectiveness rates for FCW for avoiding injury and PDO crashes to be 21 percent in both cases. Similarly, for AEB, NHTSA uses an effectiveness rate of 46 percent for injury avoidance and for PDO crashes. Effectiveness rates against non-fatal injuries and PDO crashes for the two lane-change and blind-spot technologies are shown in Table 7-8 and Table 7-9. For the two frontal-impact technologies, the central effectiveness rate noted in Table 7-7 was used rather than the reduced rates that were applied against fatalities. That is, NHTSA assumes that effectiveness against crashes is a reasonable proxy for effectiveness against non-fatal injuries and PDO crashes. 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

When equipped, the impact these technologies will have on safety is a function of: (1) their effectiveness rates and (2) the share of occupant fatalities that occur under circumstances that are relevant to the technologies' functionality (*i.e.*, the target population). Previously, NHTSA used target population estimates from a study by Wang (2019). Using 2011–2015 data from NHTSA's FARS, (NASS), and GES, the study estimated the target population and effectiveness rates specifically for a variety of crash avoidance technologies. Wang calculated target populations for five groups of collision avoidance technologies in passenger vehicles, including: forward collision mitigation, lane keeping, blind zone detection, forward pedestrian impact avoidance, and backing collision avoidance. The first three items 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. FARS and CRSS data were the basis for fatal crashes, while non-fatal injuries and PDOs were derived from the CRSS data. Wang followed the pre-crash typology concept initially developed by Volpe. Under this concept, crashes are categorized into mutually exclusive and distinct scenarios based on vehicle movements and critical events occurring just prior to the crash.

For this analysis, NHTSA has updated Wang's estimates using data from NHTSA's FARS and CRSS for 2017–2022.

Table 7-5 summarizes the portion of total annual crashes and injuries for each crash severity category that is relevant to the three crash scenarios examined using information from crashes occurring between 2017 and 2022.

Table 7-5: Summary of Target Crash Proportions by Technology Group

Safety System Crash Type	Crashes	Fatalities	MAIS 1–5 Injuries	PDOV*s
Frontal Crashes	29.4%	1.1%	30.6%	36.9%
Lane Departure Crashes	22.7%	44.9%	19.7%	12.8%
Blind Spot Crashes	10.6%	1.7%	8.3%	13.6%
Pedestrian Crashes	1.7%	14.4%	3.3%	1.1%

*PDOV is Property Damage Only Vehicle Crashes.

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 1.1 percent of fatal crashes occur in front-to-rear crashes, but approximately 30 percent of non-fatal crashes are this type. By contrast, fatal crashes are highly likely to involve inadvertent lane departure; 44.9 percent of all light vehicle occupant fatalities occur in crashes that involve lane departure, but only 19.7 percent of non-fatal injuries and 12.8 percent of PDOs involve this crash scenario. Blind spot crashes account for only about 1.7 percent of fatalities, 8.3 percent of maximum abbreviated injury scale (MAIS) 1–5 injuries, and 13.6 percent of PDOs.

The target population of the safety analysis of previous CAFE rulemakings have been occupants of LDVs subject to CAFE. NHTSA chose occupants of LDVs 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, NHTSA has expanded the target population to include non-occupants as well. Non-occupants in frontal crashes are captured through a separate analysis of PAEB. For lane change and BSD crashes, non-occupants are an insignificant portion of crashes; NHTSA retained the crash proportions it had developed previously for occupants. The values in Table 7-5 are portions of all crashes that occur annually. These include crashes of motor vehicles not subject to the current CAFE rulemaking (*e.g.*, medium and large trucks, buses, motorcycles, bicycles). To adjust for this, the values in Wang are normalized to represent their portion of all LD passenger vehicle crashes, rather than all crashes of any type.

Wang provides total passenger vehicle (PV) fatalities consistent with her technology numbers, which are used as a baseline for this process. Based on 2017–2022 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 the Leslie *et al.* studies. 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.

ESC has been standard equipment in all light vehicles in the United States since MY 2012. ESC is highly effective in reducing roadway departure and traction loss crashes, and though it will be present in all future model year vehicles, it was present in only about 30 percent of the 2017–2022 on-road fleet Wang examined. To reflect the impact of ESC on future on-road fleets, 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 allocation has the effect of reducing the total fatalities in both groups as well as in the total projected fatalities baseline.

Table 7-6 summarizes the revised incidence counts and recalculated proportions of total PV occupant crash/injury.

Table 7-6: Adjusted Target Crash Counts and Proportions 2017–2022

Crash Type	Crashes	Fatalities	MAIS 1–5	PDOVs
Frontal Crashes	1,609,722	422	729,277	2,946,060
% All PV Occupant Crashes	29.4%	1.1%	30.6%	36.9%

Lane Departure Crashes	1,242,366	17,011	468,535	1,022,652
% All PV Occupant Crashes	22.7%	44.9%	19.7%	12.8%
Blind Spot Crashes	581,363	629	197,212	1,085,246
% All PV Occupant Crashes	10.6%	1.7%	8.3%	13.6%
Pedestrian Crashes	94,668	5,468	78,836	86,427
% All PV Participant Crashes	1.7%	14.4%	3.3%	1.1%
Total, All Tech Groups	3,639,194	23,599	1,501,894	5,334,102
Total, % All PV Occupant Crashes	66.4%	62.3%	63.0%	66.8%
All Crashes	5,483,182	37,906	2,383,410	7,982,226

7.2.5. Fleet Penetration Schedules

The third element of NHTSA’s safety projections for ADAS are 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. To varying degrees, these technologies are already being installed on some vehicles, but the agency expects that, over time, they will become standard equipment due to a combination of market pressure and 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 pace of adoption in recent years. These published data were obtained from Ward’s Automotive Reports for each technology up to MY 2024. Since the deployment of these technologies is relatively recent, only a few years of data—typically two or three years—were available from which to derive a trend. Given this limited dataset, but under these circumstances, a continuation of the known trend is the baseline assumption, which NHTSA modifies only when there is a rationale to justify it. Since the deployment of these technologies is relatively recent, only a few years of data—typically two or three years—were available from which to derive a trend. Given this limited dataset, but under these circumstances, a continuation of the known trend is the baseline assumption, which NHTSA modifies 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 of adoption are expected to diverge significantly due to a formal agreement brokered by NHTSA and IIHS, involving nearly all auto manufacturers, to have had AEB installed in 100 percent of their vehicles by September 2022 (MY 2023).⁸⁰⁵ Ward’s first published installation rates for FCW and AEB are for MY 2016. As of this analysis, the MY 2024 is the latest data they have published. NHTSA thus has data indicating that FCW was installed in 17.6 percent of MY

⁸⁰⁵ NHTSA, NHTSA-IIHS Announcement on AEB, last revised: Dec. 21, 2017, available at: <https://www.nhtsa.gov/press-releases/nhtsa-iihs-announcement-aeb> (accessed: May 21, 2026).

2016 vehicles and 100 percent of MY 2024 vehicles. By 2021, all vehicles with FCW also incorporated AEB. AEB was installed in 12.0 percent of MY 2016 vehicles and 97.3 percent of MY 2024 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 20 manufacturers equipped more than 75 percent of their new passenger vehicles with AEB. Overall, manufacturers equipped more than 13.5 million new passenger vehicles with AEB.⁸⁰⁶

Because of voluntary industry commitment, NHTSA assumes that some form of AEB will be in nearly all light vehicles by MY 2025. To derive installation rates for MY 2025 and beyond, NHTSA assumes 100-percent AEB installation.

For LDW, Ward’s penetration data were available dating back as far as MY 2013, giving a total of 9 data points through MY 2024. The projection for LDW was derived by modelling these data points. The data indicate a near linear trend, with NHTSA’s initial projections of future years derived directly from this model. Ward did not report any of the more advanced LKA systems until MY 2016, leaving only six data points through MY 2024. 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 that NHTSA will allow 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 on BSD were available for MYs 2013-2024. NHTSA used Reverse Collision Detection (RCD) in Ward’s as a proxy for LCA installations because 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 MY 2016 vehicles.⁸⁰⁷ BSD is calculated as the difference between Blind Spot Alert (BSA) reported in Ward’s and RCD, as BSA includes both BSD and LCA systems. From this, NHTSA was able to measure the installation rates of BSD and LCA systems for MYs 2016-2024. As with frontal and lane change technologies, the agency assumes a gradual phase-in of the most effective technology, LCA, which will eventually replace the lesser technology, BSD. The agency will allow gradual increases in market penetration for both systems 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 MYs 2016-2024. PAEB was introduced in 2015 and was initially set to 0 in the table. A linear extrapolation of the data suggests that installation of PAEB will be 100 percent by MY 2024 given the shared hardware with AEB. Values for subsequent model years are assumed to be 100 percent.

7.2.6. Impact Calculations

Table 7-7, Table 7-8, Table 7-9, and Table 7-10 summarize the resulting estimates of impacts on fatality rates for frontal crash technologies, lane change technologies, blind spot technologies, and pedestrian collision mitigation technologies for MYs 2015-2031. 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. Because 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

⁸⁰⁶ NHTSA, NHTSA Announces Update to Historic AEB Commitment by 20 Automakers, last revised: Dec. 17, 2020, available at: <https://www.nhtsa.gov/press-releases/nhtsa-announces-2020-update-aeb-installation-20-automakers> (accessed: May 21, 2026).

⁸⁰⁷ Threewitt, C., 10 Cars With Lane Assist Using Cameras or Sensors, last revised: Apr. 5, 2016, available at: <https://www.autoweek.com/10-cars-with-lane-change-assist-using-cameras-or-sensors> (accessed: May 21, 2026).

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 six technologies for each model year. These cumulative results are shown in the last column of Table 7-10. As technologies phase into newer model year fleets,⁸⁰⁸ their impact on the LDV occupant fatality rate increases proportionally to roughly 11.9 percent before levelling off. By MY 2026, NHTSA expects these technologies to reduce fatalities and fatality rates for new vehicles by 12 percent relative to a scenario in which they were never deployed.

Table 7-7: 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	1.1%	8.30199E-05
2016	10.5%	0.056	23.0%	0.120	1.1%	0.000373022
2017	10.5%	0.035	23.0%	0.270	1.1%	0.000731302
2018	10.5%	0.021	23.0%	0.445	1.1%	0.001163696
2019	10.5%	0.018	23.0%	0.583	1.1%	0.001512034
2020	10.5%	0.006	23.0%	0.741	1.1%	0.0019027
2021	10.5%	0.001	23.0%	0.816	1.1%	0.002088772
2022	10.5%	0.000	23.0%	0.882	1.1%	0.002257311
2023	10.5%	0.000	23.0%	0.877	1.1%	0.002243442
2024	10.5%	0.000	23.0%	0.973	1.1%	0.002488421
2025	10.5%	0.000	23.0%	1	1.1%	0.002557881
2026	10.5%	0.000	23.0%	1	1.1%	0.002557881
2027	10.5%	0.000	23.0%	1	1.1%	0.002557881
2028	10.5%	0.000	23.0%	1	1.1%	0.002557881
2029	10.5%	0.000	23.0%	1	1.1%	0.002557881
2030	10.5%	0.000	23.0%	1	1.1%	0.002557881
2031	10.5%	0.000	23.0%	1	1.1%	0.002557881

Table 7-8: 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	44.9%	0.007931027
2016	10.0%	0.110	20.0%	0.088	44.9%	0.012826662
2017	10.0%	0.075	20.0%	0.205	44.9%	0.021795301
2018	10.0%	0.084	20.0%	0.324	44.9%	0.032876997
2019	10.0%	0.037	20.0%	0.442	44.9%	0.041338144

⁸⁰⁸ 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.

2020	10.0%	0.092	20.0%	0.586	44.9%	0.056748135
2021	10.0%	0.110	20.0%	0.650	44.9%	0.06329772
2022	10.0%	0.090	20.0%	0.722	44.9%	0.068824844
2023	10.0%	0.086	20.0%	0.751	44.9%	0.071289536
2024	10.0%	0.069	20.0%	0.861	44.9%	0.080368651
2025	10.0%	0.053	20.0%	0.947	44.9%	0.087367712
2026	10.0%	0	20.0%	1	44.9%	0.089752591
2027	10.0%	0	20.0%	1	44.9%	0.089752591
2028	10.0%	0	20.0%	1	44.9%	0.089752591
2029	10.0%	0	20.0%	1	44.9%	0.089752591
2030	10.0%	0	20.0%	1	44.9%	0.089752591
2031	10.0%	0	20.0%	1	44.9%	0.089752591

Table 7-9: 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	1.7%	0.000102426
2016	3.0%	0.311	26.0%	0.000	1.7%	0.000154604
2017	3.0%	0.389	26.0%	0.000	1.7%	0.000193404
2018	3.0%	0.398	26.0%	0.051	1.7%	0.000416104
2019	3.0%	0.459	26.0%	0.095	1.7%	0.000639244
2020	3.0%	0.446	26.0%	0.163	1.7%	0.000925674
2021	3.0%	0.453	26.0%	0.256	1.7%	0.001331796
2022	3.0%	0.448	26.0%	0.283	1.7%	0.001442414
2023	3.0%	0.362	26.0%	0.346	1.7%	0.001671029
2024	3.0%	0.359	26.0%	0.438	1.7%	0.002066415
2025	3.0%	0.337	26.0%	0.481	1.7%	0.002244533
2026	3.0%	0.349	26.0%	0.525	1.7%	0.00243927
2027	3.0%	0.361	26.0%	0.569	1.7%	0.002634007
2028	3.0%	0.373	26.0%	0.613	1.7%	0.002828744
2029	3.0%	0.344	26.0%	0.656	1.7%	0.003002755
2030	3.0%	0.300	26.0%	0.700	1.7%	0.003169752
2031	3.0%	0.256	26.0%	0.744	1.7%	0.003336748

Table 7-10: 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	14.4%	0.00%	0.0081165
2016	17.1%	0.074	14.4%	0.18%	0.0151828
2017	17.1%	0.179	14.4%	0.44%	0.0271575
2018	17.1%	0.310	14.4%	0.77%	0.0421096
2019	17.1%	0.458	14.4%	1.13%	0.0548116
2020	17.1%	0.638	14.4%	1.58%	0.0753506
2021	17.1%	0.746	14.4%	1.85%	0.0851704
2022	17.1%	0.831	14.4%	2.05%	0.0930668
2023	17.1%	0.848	14.4%	2.10%	0.0961740
2024	17.1%	0.939	14.4%	2.32%	0.1081375
2025	17.1%	1.000	14.4%	2.47%	0.1168946
2026	17.1%	1.000	14.4%	2.47%	0.1194742
2027	17.1%	1.000	14.4%	2.47%	0.1196689
2028	17.1%	1.000	14.4%	2.47%	0.1198637
2029	17.1%	1.000	14.4%	2.47%	0.1200377
2030	17.1%	1.000	14.4%	2.47%	0.1202047
2031	17.1%	1.000	14.4%	2.47%	0.1203717

The inputs and weighted effectiveness for non-fatal injuries are summarized in Table 7-11 through Table 7-14 and for PDOs in Table 7-15 through Table 7-18.⁸⁰⁹

Table 7-11: Phased Impact of Crashworthiness Technologies on Non-Fatal Injury Rates, Forward Collision Crashes

MY	Forward Collision Warning		Automatic Emergency Braking		% T.P.	Weighted Effectiveness
	Eff.	% Inst.	Eff.	% Inst.		
2015	21.0%	0.047	46.0%	0.011	30.6%	0.004568289
2016	21.0%	0.056	46.0%	0.120	30.6%	0.020526066
2017	21.0%	0.035	46.0%	0.270	30.6%	0.040240912
2018	21.0%	0.021	46.0%	0.445	30.6%	0.064034046
2019	21.0%	0.018	46.0%	0.583	30.6%	0.083201815
2020	21.0%	0.006	46.0%	0.741	30.6%	0.104698772
2021	21.0%	0.001	46.0%	0.816	30.6%	0.114937644
2022	21.0%	0.000	46.0%	0.882	30.6%	0.124211731
2023	21.0%	0.000	46.0%	0.877	30.6%	0.123448615
2024	21.0%	0.000	46.0%	0.973	30.6%	0.136928903
2025	21.0%	0.000	46.0%	1	30.6%	0.140751033
2026	21.0%	0.000	46.0%	1	30.6%	0.140751033
2027	21.0%	0.000	46.0%	1	30.6%	0.140751033

⁸⁰⁹ See previous discussion in this subchapter for the studies and methodology used to create these estimates.

2028	21.0%	0.000	46.0%	1	30.6%	0.140751033
2029	21.0%	0.000	46.0%	1	30.6%	0.140751033
2030	21.0%	0.000	46.0%	1	30.6%	0.140751033
2031	21.0%	0.000	46.0%	1	30.6%	0.140751033

Table 7-12: 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	19.7%	0.003474207
2016	10.0%	0.110	20.0%	0.088	19.7%	0.005618753
2017	10.0%	0.075	20.0%	0.205	19.7%	0.009547489
2018	10.0%	0.084	20.0%	0.324	19.7%	0.014401854
2019	10.0%	0.037	20.0%	0.442	19.7%	0.018108282
2020	10.0%	0.092	20.0%	0.586	19.7%	0.024858669
2021	10.0%	0.110	20.0%	0.650	19.7%	0.027727732
2022	10.0%	0.090	20.0%	0.722	19.7%	0.030148903
2023	10.0%	0.086	20.0%	0.751	19.7%	0.031228568
2024	10.0%	0.069	20.0%	0.861	19.7%	0.035205698
2025	10.0%	0.053	20.0%	0.947	19.7%	0.038271655
2026	10.0%	0	20.0%	1	19.7%	0.039316358
2027	10.0%	0	20.0%	1	19.7%	0.039316358
2028	10.0%	0	20.0%	1	19.7%	0.039316358
2029	10.0%	0	20.0%	1	19.7%	0.039316358
2030	10.0%	0	20.0%	1	19.7%	0.039316358
2031	10.0%	0	20.0%	1	19.7%	0.039316358

Table 7-13: 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	8.3%	0.000510747
2016	3.0%	0.311	26.0%	0.000	8.3%	0.000770935
2017	3.0%	0.389	26.0%	0.000	8.3%	0.000964411
2018	3.0%	0.398	26.0%	0.051	8.3%	0.002074908
2019	3.0%	0.459	26.0%	0.095	8.3%	0.003187598
2020	3.0%	0.446	26.0%	0.163	8.3%	0.004615885
2021	3.0%	0.453	26.0%	0.256	8.3%	0.006641017
2022	3.0%	0.448	26.0%	0.283	8.3%	0.007192616

2023	3.0%	0.362	26.0%	0.346	8.3%	0.008332606
2024	3.0%	0.359	26.0%	0.438	8.3%	0.010304199
2025	3.0%	0.337	26.0%	0.481	8.3%	0.011192386
2026	3.0%	0.349	26.0%	0.525	8.3%	0.012163444
2027	3.0%	0.361	26.0%	0.569	8.3%	0.013134503
2028	3.0%	0.373	26.0%	0.613	8.3%	0.014105561
2029	3.0%	0.344	26.0%	0.656	8.3%	0.01497327
2030	3.0%	0.300	26.0%	0.700	8.3%	0.015806001
2031	3.0%	0.256	26.0%	0.744	8.3%	0.016638731

Table 7-14: 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	3.3%	0.000000	0.86%	1.053812889
2016	25.0%	0.074	3.3%	0.000612	2.75%	1.813060576
2017	25.0%	0.179	3.3%	0.001484	5.22%	1.923483188
2018	25.0%	0.310	3.3%	0.002560	8.31%	1.972717864
2019	25.0%	0.458	3.3%	0.003787	10.83%	1.975576935
2020	25.0%	0.638	3.3%	0.005276	13.94%	1.850670257
2021	25.0%	0.746	3.3%	0.006171	15.55%	1.825490827
2022	25.0%	0.831	3.3%	0.006870	16.84%	1.809708326
2023	25.0%	0.848	3.3%	0.007014	17.00%	1.76787161
2024	25.0%	0.939	3.3%	0.007764	19.02%	1.758897991
2025	25.0%	1.000	3.3%	0.008269	19.85%	1.697977292
2026	25.0%	1.000	3.3%	0.008269	20.05%	1.6781875
2027	25.0%	1.000	3.3%	0.008269	20.15%	1.683571128
2028	25.0%	1.000	3.3%	0.008269	20.24%	1.688937263
2029	25.0%	1.000	3.3%	0.008269	20.33%	1.693717555
2030	25.0%	1.000	3.3%	0.008269	20.41%	1.698292133
2031	25.0%	1.000	3.3%	0.008269	20.50%	1.702854017

Table 7-15: 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	35.9%	0.005364169
2016	21.0%	0.056	46.0%	0.120	35.9%	0.024102084

2017	21.0%	0.035	46.0%	0.270	35.9%	0.047251616
2018	21.0%	0.021	46.0%	0.445	35.9%	0.075189952
2019	21.0%	0.018	46.0%	0.583	35.9%	0.097697097
2020	21.0%	0.006	46.0%	0.741	35.9%	0.122939219
2021	21.0%	0.001	46.0%	0.816	35.9%	0.13496189
2022	21.0%	0.000	46.0%	0.882	35.9%	0.145851693
2023	21.0%	0.000	46.0%	0.877	35.9%	0.144955628
2024	21.0%	0.000	46.0%	0.973	35.9%	0.16078443
2025	21.0%	0.000	46.0%	1	35.9%	0.165272445
2026	21.0%	0.000	46.0%	1	35.9%	0.165272445
2027	21.0%	0.000	46.0%	1	35.9%	0.165272445
2028	21.0%	0.000	46.0%	1	35.9%	0.165272445
2029	21.0%	0.000	46.0%	1	35.9%	0.165272445
2030	21.0%	0.000	46.0%	1	35.9%	0.165272445
2031	21.0%	0.000	46.0%	1	35.9%	0.165272445

Table 7-16: 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	14.0%	0.002479886
2016	10.0%	0.110	20.0%	0.088	14.0%	0.004010661
2017	10.0%	0.075	20.0%	0.205	14.0%	0.006814989
2018	10.0%	0.084	20.0%	0.324	14.0%	0.010280031
2019	10.0%	0.037	20.0%	0.442	14.0%	0.012925676
2020	10.0%	0.092	20.0%	0.586	14.0%	0.017744096
2021	10.0%	0.110	20.0%	0.650	14.0%	0.019792031
2022	10.0%	0.090	20.0%	0.722	14.0%	0.021520261
2023	10.0%	0.086	20.0%	0.751	14.0%	0.022290925
2024	10.0%	0.069	20.0%	0.861	14.0%	0.025129797
2025	10.0%	0.053	20.0%	0.947	14.0%	0.027318274
2026	10.0%	0	20.0%	1	14.0%	0.028063982
2027	10.0%	0	20.0%	1	14.0%	0.028063982
2028	10.0%	0	20.0%	1	14.0%	0.028063982
2029	10.0%	0	20.0%	1	14.0%	0.028063982
2030	10.0%	0	20.0%	1	14.0%	0.028063982
2031	10.0%	0	20.0%	1	14.0%	0.028063982

Table 7-17: 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	14.5%	0.000892017
2016	3.0%	0.311	26.0%	0.000	14.5%	0.001346434
2017	3.0%	0.389	26.0%	0.000	14.5%	0.001684338
2018	3.0%	0.398	26.0%	0.051	14.5%	0.003623814
2019	3.0%	0.459	26.0%	0.095	14.5%	0.005567121
2020	3.0%	0.446	26.0%	0.163	14.5%	0.008061615
2021	3.0%	0.453	26.0%	0.256	14.5%	0.011598496
2022	3.0%	0.448	26.0%	0.283	14.5%	0.01256186
2023	3.0%	0.362	26.0%	0.346	14.5%	0.014552847
2024	3.0%	0.359	26.0%	0.438	14.5%	0.017996222
2025	3.0%	0.337	26.0%	0.481	14.5%	0.019547436
2026	3.0%	0.349	26.0%	0.525	14.5%	0.021243383
2027	3.0%	0.361	26.0%	0.569	14.5%	0.02293933
2028	3.0%	0.373	26.0%	0.613	14.5%	0.024635278
2029	3.0%	0.344	26.0%	0.656	14.5%	0.026150727
2030	3.0%	0.300	26.0%	0.700	14.5%	0.027605086
2031	3.0%	0.256	26.0%	0.744	14.5%	0.029059445

Table 7-18: 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	0.87%	1.076338492
2016	0.1%	0.074	0.1%	0.000000	2.95%	1.940304334
2017	0.1%	0.179	0.1%	0.000000	5.58%	2.052880156
2018	0.1%	0.310	0.1%	0.000000	8.91%	2.115764688
2019	0.1%	0.458	0.1%	0.000000	11.62%	2.119811122
2020	0.1%	0.638	0.1%	0.000000	14.87%	1.974043383
2021	0.1%	0.746	0.1%	0.000000	16.64%	1.953176227
2022	0.1%	0.831	0.1%	0.000000	17.99%	1.933389087
2023	0.1%	0.848	0.1%	0.000000	18.18%	1.890321903
2024	0.1%	0.939	0.1%	0.000001	20.39%	1.88566345
2025	0.1%	1.000	0.1%	0.000001	21.21%	1.814786899
2026	0.1%	1.000	0.1%	0.000001	21.46%	1.796039762
2027	0.1%	1.000	0.1%	0.000001	21.63%	1.807289064

2028	0.1%	1.000	0.1%	0.000001	21.80%	1.818501814
2029	0.1%	1.000	0.1%	0.000001	21.95%	1.828490423
2030	0.1%	1.000	0.1%	0.000001	22.09%	1.838049182
2031	0.1%	1.000	0.1%	0.000001	22.24%	1.847581419

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 reduce non-fatal injuries and property damage crashes by more than they reduce fatalities.⁸¹⁰

7.2.7. Impact of Advanced Technologies on Older Vehicles' Fatality Rates

Generally, the users of older vehicles benefit from crash avoidance technologies when new vehicles are equipped with these technologies as they prevent multi-vehicle crashes. The scope of these impacts on fatality rates in older vehicles is limited due to several factors.

About half of all fatal crashes are single-vehicle crashes, and involve older vehicles. The other half of fatalities occur in multi-vehicle crashes. ADAS can affect outcomes in crashes involving a newer vehicle with advanced technology and an older vehicle.

For a new safety technology to benefit an older vehicle in a multi-vehicle crash, the vehicle with the technology must be able to control or prevent the crash. For example, in front-to-rear crashes that can be addressed by FCW and AEB, the older vehicle can benefit only if the vehicle is at risk of being struck from behind. If the struck vehicle is a newer vehicle, its AEB technology cannot prevent the crash. Logically this occurs in roughly half of two-vehicle crashes and a third of all three-vehicle crashes.

For older vehicles, the benefits are proportional to the probability that the vehicles with which they collide have advanced crash avoidance technology. One caveat: it is not possible to anticipate an exhaustive list of other possible real-world scenarios. NHTSA lacks the data to estimate the frequency at which false positive events occur, as well as the frequency at which false positives result in negative safety outcomes. NHTSA assumes that ADAS technologies should not take unanticipated action or intervene in non-crash imminent scenarios. NHTSA estimates that the probability that this occurs is a function of the relative exposure of vehicles by age, measured by the portion of total VMT by vehicles of that age. Based on VMT schedules (see CY 2016 example in Table 7-19), new (current model year) vehicles account for about 9.6 percent of annual fleet VMT. The relevant portion increases 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 ($0.5 \times 0.5 \times 0.096$) of older vehicles involved in crashes benefit from advanced crash avoidance technologies in other vehicles in the first year.

Table 7-19: 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

⁸¹⁰ For example, for MY 2031, the combined effectiveness for PDO crashes is 22.24 percent, as shown in the second to last column of Table 7-23, which is 1.847 times the 12.04-percent combined effectiveness for fatalities, as seen in Table 7-15, which shows the disproportionality impact of crash avoidance technologies on non-fatal accidents.

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
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
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To reflect this safety benefit for older vehicles, NHTSA calculates a revised fatality rate for each older model year vehicle on the road based on its interaction with each new model year starting with MY 2021 vehicles based on the following relationship.

Equation 7-1: Fatality Rate Adjusted for Crash Avoidance Technologies

$$\text{Revised Fatality Rate} = Fm((x-y)mnp) + F(1-m)$$

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 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) is 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 are measured. It establishes the baseline rate for each model year that are compared to the most current model year rate, determining the change in fatality rate 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 ESC, but through MY 2017, crashworthiness standards are the predominate cause of these differences.

The most recent significant crashworthiness safety standard, which upgrades roof strength standards, is effective in all new passenger vehicles as of MY 2017. Crashworthiness standards do not have secondary benefits for older model year vehicles. For MY 2017 and beyond, NHTSA assumes crash avoidance technologies drive safety improvements. To isolate the added crash avoidance safety expected in newer vehicles, the marginal impact of the difference between the MY 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 MY 2017 and earlier. Beginning with MY 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 from non-technology factors.

Of PV occupant fatalities, the proportion that occurs in multi-vehicle crashes (m), is derived from an analysis of occupants in fatal PV crashes from 2002 to 2017 in FARS. The analysis indicates that 47.8 percent of fatal crash occupants are in single-vehicle crashes, 40.2 percent are in two-vehicle crashes, and

12 percent are in crashes involving three or more vehicles. Overall, 52.2 percent are 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 7-19), the most current model year will represent 9.6 percent of all VMT in a calendar year, implying a 9.6-percent probability that the vehicle encounters will be from the most current model year. This percentage will increase for each calendar year as more model year vehicles adopt advanced crashworthiness technologies. Other factors that are the basis for NHTSA’s VMT proportion table, such as uneven concentrations of newer vs. older vehicles or improved crash avoidance in the younger vehicles already on the road, might disrupt this assumption. Ultimately, this is a lenient 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) is calculated using the relative frequency of fatal crash occupants in multi-vehicle crashes. As noted previously, 40.2 percent are in two-vehicle crashes, and 12 percent are in crashes involving three or more vehicles. NHTSA assumes a probability of 50 percent for two vehicle crashes and 33 percent for crashes with three or more vehicles. Weighted together, NHTSA estimates 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 7-20 below for adjustments due to improvements in MY 2021 vehicles back through MY 1995. In Table 7-20 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 MY 2017 rate for all model years prior to MY 2018, after which it becomes the actual model year rate. Column 4 shows the difference between the fatality rate for MY 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-MY 2018 vehicles’ fatality rates, with declining impacts going forward to MY 2021. In subsequent years, this impact will grow to reflect both the increased probability that an older vehicle will be involved in crashes with vehicles equipped with advanced technology, as well as the increased technology levels in progressively newer vehicles.⁸¹¹ The CAFE Model uses updated inputs applicable to this final rule to reflect revised fatality rate trends going forward along with covering even older model years. These same adjustments are reflected for non-fatal injuries and PDO crashes.

Table 7-20: 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

⁸¹¹ Table 7-25 was created using inputs from the 2020 CAFE NPRM and is provided for explanatory purposes only.

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

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 state that they will continue to reduce vehicle mass to meet standards for a given set of vehicle models, and therefore, this expectation is incorporated into the modeling analysis supporting the standards. Some 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,⁸¹² mass reduction concentrated among the heaviest vehicles (chiefly, the largest LTVs, CUVs and minivans) is estimated to reduce overall fatalities, while mass reduction concentrated among the lightest vehicles (chiefly, smaller passenger cars) is estimated to increase overall fatalities. Past NHTSA analyses consistently indicate that increasing the disparity of the masses of vehicles is harmful to safety. In collisions among multiple 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 heavier vehicles. Reducing mass simultaneously across multiple vehicles has a range of net effects; for example, proportional mass reduction across the vehicle fleet will be expected to have a roughly neutral effect on the total number of fatalities in any given year, more commonly referred to as the “societal fatality risk,” for two-vehicle crashes. This highlights the role of mass disparity in societal fatality risk: as the overall vehicle fleet moves closer together in terms of mass (or, as measured in this 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 are capable of coordinating and reducing mass equally across all vehicles in the new vehicle fleet, new vehicles will 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 will be considered in representing the effects of mass reduction on societal fatality rates.

In response to questions of whether designs and materials of more recent model year vehicles weaken the historical statistical relationships between mass, size, and safety, NHTSA updates its public database for statistical analysis consisting of crash data. The database incorporates the full range of real-world crash types. NHTSA sponsors a study, discussed in Chapter 7.2.5, conducted by George Washington University (GWU) to develop a fleet simulation model and to study the impact and relationship of light-weighted vehicle design with crash injuries and fatalities. 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 does 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), is 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 does 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 disparity are associated with changes in motor vehicle safety: increased disparity increases fatality risk, while decreased disparity decreases risk.

⁸¹² Kahane, C. J., Relationships Between Vehicle Size and Fatality Risk in Model Year 1985-93 Passenger Cars and Light Trucks, NHTSA Technical Report No. DOT HS 808 570, NHTSA: Washington, D.C. (1997), available at: <https://rosap.nhtl.bts.gov/view/dot/8727> (accessed: May 21, 2026); Kahane, C. J., Vehicle Weight, Fatality Risk and Crash Compatibility of Model Year 1991-99 Passenger Cars and Light Trucks, Report No. DOT HS 809 662, NHTSA: Washington, D.C. (2003), available at: <https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/809662> (accessed: May 21, 2026); Kahane, C. J., NHTSA, Final Regulatory Impact Analysis: Corporate Average Fuel Economy for MY 2012-MY 2016 Passenger Cars and Light Trucks, NHTSA: Washington, D.C. (2010), available at: https://www.nhtsa.gov/sites/nhtsa.gov/files/2022-02/CAFE_2012-2016_FRIA_04012010.pdf (accessed: May 21, 2026); Kahane, C.J., Relationships Between Fatality Risk, Mass, and Footprint in Model Year 2000-2007 Passenger Cars and LTVs, Report No. DOT-HS-811-665, NHTSA: Washington, D.C. (2012), available at: <https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/811665> (accessed: May 21, 2026); Puckett, S. M. & Kindelberger, J. C., Relationships between Fatality Risk, Mass, and Footprint in Model Year 2003-2010 Passenger Cars and LTVs, Preliminary Report, Docket No. NHTSA-2016-0068 (2016), available at <https://www.nhtsa.gov/sites/nhtsa.gov/files/2016-prelim-relationship-fatalityrisk-mass-footprint-2003-10.pdf> (accessed: May 21, 2026).

The CAFE standards for LDVs are “footprint-based,” with footprint 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), the average footprint of LDVs (and the most common pickups with GVWR above 8,500 pounds) increases 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 increase as footprint decreases. NHTSA develops the curves with the intent to minimize the incentive for manufactures to achieve compliance by reducing the footprint of vehicles. Several technologies, such as the 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. Mass reductions of 100 pounds are considered in the analyses as a matter of convention; considering smaller magnitudes of mass reduction will not change meaningfully either for focal vehicle classes or for the fleet at large (*i.e.*, in terms of mass disparity). This process allows the CAFE Model to tally changes in fatalities attributed to mass reduction across all future model years analyzed. In turn, the CAFE Model provides 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 is 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.

The mass-size-safety analysis groups vehicles by body type with the objective of estimating common relationships (split by threshold curb weight) specific to that body type, where feasible. That is, the analysis estimates one relationship for passenger cars, another for SUVs, and another for CUVs and minivans, the latter of which contains too few vehicles to be evaluated on their own. The decision to specify vehicle safety classes this way involves trading some degree of likeness with CAFE regulatory classes to maintain physical similarity within vehicle classes.

The distinction above is most relevant to CUVs and compact SUVs that would be reclassified from light trucks to passenger cars in projected years in the CAFE Model under this final rulemaking. The estimated relationships between curb weight and societal fatality risk apply to the vehicles within a given safety class independently of those vehicles’ corresponding CAFE regulatory classes. In turn, the estimated mass-size-safety relationships associated with a given cohort of CUVs and compact SUVs in the base year (when these vehicles are classified as light trucks) would apply in any out-years during which the vehicles are classified as passenger cars.

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 this final rule uses is carried forward from the 2020, 2022, and 2024 CAFE rules, and reflects learning 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 rulemakings in 2010, 2012, the 2016 Draft TAR, and the 2020 rulemaking. As explained in greater detail below, the methodology uses the statistical analysis of historical crash data for this final rule as 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 concentrates 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 concentrates among the heaviest vehicles will 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 rulemakings, each of these estimated relationships represents the 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.⁸¹³ 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.

Following the publication of the MYs 2012-2016 rule in 2010, 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 use 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.

Second, NHTSA and EPA, in consultation with DOE, would update the MYs 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.

Third, NHTSA would seek 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.

By the time of the MYs 2017-2025 final rule, significant progress had been made on these tasks. An independent review of then-recent statistical analyses of the relationship between vehicle mass, size, and crash fatality rates had been completed by UMTRI. UMTRI evaluated more than 20 academic papers,

⁸¹³ Nine types of crashes are 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; or truck-based LTVs. All other fatal crash types include collisions involving more than two vehicles, animals, trains, and other crash types.

including studies done by NHTSA’s Kahane, Wenzel of DOE’s Lawrence Berkeley National Laboratory (LBNL), Dynamic Research, Inc. (DRI), and others. UMTRI’s basic findings are discussed below.

To support rulemaking efforts, NHTSA created a common, updated database for statistical analysis consisting of crash data of MYs 2000-2007 vehicles in CYs 2002-2008, as compared to the database used in prior NHTSA analyses, which was based on MYs 1991-1999 vehicles in CYs 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 starting with the 2021 NPRM.

NHTSA is aware of several studies that have been initiated using the 2011 version or the 2012 version of NHTSA’s safety database. In addition to new Kahane studies, other recent and on-going studies included two by Wenzel at LBNL under contract with the 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 MYs 2004-2011 vehicles during CYs 2006-2012. As in previous analyses, NHTSA has made the databases available to the public on its website.⁸¹⁴

NHTSA has continued to sponsor new studies and research to inform the current CAFE rulemaking. In addition, NAS published reports that include discussions of relationships between vehicle mass and societal fatality risk.⁸¹⁵ The 2015 NAS report summarizes results from studies by NHTSA, DRI, and the LBNL, confirming the general relationships between vehicle mass disparity and societal fatality risk (*i.e.*, mass reduction in the lightest vehicles is detrimental, and mass reduction 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 future 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) hybrid powertrains could yield different safety relationships from those identified in relevant studies.

⁸¹⁴ See NHTSA File Downloads at <https://www.nhtsa.gov/content/nhtsa-ftp/191> (accessed: May 21, 2025), for access to the databases and other files and documentation associated with CAFE rulemaking.

⁸¹⁵ NRC (2015); National Research Council, Assessment of Technologies for Improving Light-Duty Fuel Economy 2025-2035, National Academies Press: Washington, D.C. (2021), available at: <https://doi.org/10.17226/26092> (accessed: May 21, 2026).

These efforts have led to advancements in the statistical analysis research of historical crash data and have informed NHTSA’s analysis supporting this final rule, even as research in this important area continues. In establishing standards, all available data, studies, and objective information without regard to whether they were sponsored by NHTSA, are considered.

The following table presents a summary of key findings from two NHTSA workshops and several mass-size-safety publications from the 2010s:

Table 7-21: Summary of Key Findings from Mass-Size-Safety Workshops and Publications

Event/Publication	Key Findings
2011 NHTSA Workshop on Vehicle Mass, Size, and Safety	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 (<i>e.g.</i>, ESC or airbags). 3. The physics of a two-vehicle crash require the lighter vehicle to experience a greater change in velocity, which, all else being equal, 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 exists on whether smaller, lighter vehicles maneuver better, and thus avoid more crashes, than larger, heavier vehicles. 6. Kahane’s 2010 report found that a scenario that 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 it noted that if analyses were able to consider the mass of both vehicles in a two-vehicle crash, results may be more indicative of future crashes.
UMTRI Report	1. 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. 2. 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.
2012 LBNL Phase 1 Report	1. Other vehicle attributes, driver characteristics, and crash circumstances were associated with much larger changes in risk than mass reduction. 2. 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.
2012 LBNL Phase 2 Report	1. Mass reduction was associated with increases in crash frequency and decreases in fatality or serious injury risk per crash. 2. 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>i.e.</i>, though 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 (<i>e.g.</i>, omitted variables bias).
2012 DRI Reports	1. DRI replicated results from the 2003 Kahane report. 2. Results from DRI’s two-stage model were comparable to LBNL’s Phase 2 analysis. 3. 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, mass reduction was estimated to have less harmful (<i>e.g.</i>, for the lightest passenger cars) or more beneficial (<i>e.g.</i>, for the heaviest LTVs) impacts on societal fatality risk.
2012 Kahane Report	NHTSA found the 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.

2013 NHTSA Workshop on Vehicle Mass, Size, and Safety	1. Kahane: The physics of crashes, in particular conservation of momentum and equal and opposite forces, implies mass reduction in the heaviest vehicles and mass increase in the lightest vehicles can reduce societal risk in two-vehicle crashes. 2. Wenzel: 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. Further, mass reduction is associated with an increase in crash frequency but a decrease in risk per crash. 3. Van Auken: Replacing footprint with its components 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. Mass reduction is associated with an increase in crash frequency but with a decrease in risk per crash. 4. Nusholtz of Chrysler: Some assertions of mass having negligible (or purely negative) effects on safety lead to absurd conclusions in the extreme. Mass is a dominant factor in crashes, but crush space could begin to dominate if vehicles could be made larger. Safety implications of mass reduction are transition issues of greater importance so long as legacy heavier vehicles are used in significant numbers. Mass can affect crash outcomes and likelihood. Crash parameters (<i>e.g.</i>, closing speed) necessarily dominate. 5. Nolan: Safety technologies have enhanced the safety of current small cars to the level only achieved by larger cars in the past. Smaller vehicles will always be at a disadvantage, but further technological advances, such as crash avoidance systems hold promise in advancing safety.
2016 LBNL Phase 1 Report	1. 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. 2. 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. 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.
2015 NAS Report	1. The estimates of mass reductions in the CAFE Model are conservative for cars; the NAS Committee projected mass reductions between 5-percent (for small and large cars) and 6.5-percent (for mid-size cars) larger than the estimates of mass reductions in the CAFE Model. 2. Negative safety effects may occur as mass reduction takes place because of variances in how reductions occurred.
2017 National Bureau of Economic Research (NBER) Working Paper	Decreases in the dispersion of curb weights have a positive effect on safety.

7.3.2. Recent NHTSA Analysis Supporting CAFE Rulemaking

As mentioned previously, NHTSA and EPA's 2012 joint final rule for MY 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 the mpg target. However, mass reduction that maintains a vehicle's footprint does not affect the mpg target like downsizing does 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 examined this relationship for decades. The safety chapter of NHTSA’s April 2012 FRIA of CAFE standards for MYs 2017-2021 passenger cars and light trucks included a statistical analysis of relationships between fatality risk, mass, and footprint in MYs 2000-2007 passenger cars, light trucks, and LTVs, based on CYs 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 that 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 concludes, as a result that any reasonable combination of mass reductions that held footprint constant in MYs 2017-2021 vehicles—concentrated, at least to some extent, in the heavier LTVs and limited in the lighter cars—will likely be approximately safety-neutral; it will 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 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 MYs 2003-2010 vehicles in CYs 2005-2011 crashes. For this regulatory analysis, databases are the most up-to-date possible (MYs 2004-2011 vehicles in CYs 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 <https://www.nhtsa.gov/laws-regulations/corporate-average-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 estimating 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, and 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 to capture accurately 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 2020, 2022, and 2024 final CAFE rules, 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 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 MYs 2027-2050.

As in the 2012 Kahane report, 2016 Puckett and Kindelberger report, the Draft TAR, and the 2020, 2022 and 2024 CAFE final 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.

For the previous rulemakings, 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 or luxury vehicle status). However, the share of AWD passenger cars in the fleet has grown in recent years.

Approximately one-quarter of the passenger cars in the database have AWD, compared to an approximately 5-percent share in the MYs 2000-2007 database. Furthermore, all other vehicle types in the analysis include AWD as an explanatory variable. After considering the model results further, NHTSA finds 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 analysis supporting the final rule.

The boundary between “lighter” and “heavier” cars is 3,201 pounds (which is the median mass of MYs 2004-2011 cars in fatal crashes in CYs 2006-2012, up from 3,106 pounds for MYs 2000-2007 cars in CYs 2002-2008 in the 2012 NHTSA safety database, and marginally up from 3,197 pounds for MYs 2003-2010 cars in CYs 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 MYs 2004-2011 median, higher than the median of 4,594 pounds for MYs 2000-2007 LTVs in CYs 2002-2008 and the

median of 4,947 pounds for MYs 2003-2010 LTVs in CYs 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: passenger cars < 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 crash partner cars, CUVs and minivans in fatal crashes in the database); cars, CUVs, or minivans $\geq 3,187$ 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 $\geq 4,360$ 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). Isolating crashes in the “all other crash types” category from crashes involving two vehicles into 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 MYs 2008-2011 vehicles in CYs 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 7-22 presents the estimated percent increase in U.S. societal fatality risk per 10 billion VMT for each 100-pound reduction in vehicle mass, while holding footprint constant, for each of the five vehicle classes.

Table 7-22: Fatality Increase (%) per 100-Pound Mass Reduction While Holding Footprint Constant - MYs 2004-2011, CYs 2006-2012

Vehicle Class	Point Estimate	95% Confidence Bounds
Cars < 3,201 pounds	1.12	-0.57 to +2.81
Cars > 3,201 pounds	0.89	-0.09 to +1.87
CUVs and minivans	-0.25	-1.55 to +1.04
Truck-based LTVs < 5,014 pounds	0.31	-0.51 to +1.13
Truck-based LTVs > 5,014 pounds	-0.61	-1.46 to +0.25

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 has 95-percent confidence bounds that exclude zero; thus, the estimated effects are not statistically significant at the 95-percent confidence level. NHTSA has evaluated these results and provided them for the purpose of transparency. Analysis of sensitivity cases has confirmed that the exclusion of these statistically insignificant results would not affect NHTSA’s policy determination, because the net effects of mass reduction on safety costs are small relative to the 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 lighter cars and (2) decrease by 0.61 percent if mass is reduced by 100 pounds in heavier trucks.

NHTSA believes that the central value estimates are the best estimates available and offer a stronger statistical representation of relationships among vehicle curb weight, footprint, and fatality risk than an assumption of no correlation whatsoever. NHTSA also presents the statistical uncertainty associated with the estimates. 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 meaningful⁸¹⁶ and are in line with the prior analyses used in past NHTSA CAFE

⁸¹⁶ 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.

rulemakings. As shown in Table 7-22, 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, or demographic characteristics), the results may become less representative. That is, though safety features and demographic factors are accounted for separately, 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 ESC, 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 considers 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 did not change from MYs 1991-1999 to MYs 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, 2022, and 2024 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 2 percent per 100-pound mass reduction and 1 square-foot footprint reduction, respectively; these three models include passenger cars and CUVs in first-event rollovers and include 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 2 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. Lighter and heavier passenger cars each have one estimated coefficient that is consistent with potential effects of multicollinearity; these coefficients are found in the models of crashes with heavier LTVs (for heavier passenger cars) and all other crashes (for lighter passenger cars).

Multicollinearity is one of the important concerns affecting 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 7-23 compares the fatality coefficients from the 2012 Kahane report (MYs 2000-2007 vehicles in CYs 2002-2008) and the 2016 Puckett and Kindelberger report and Draft TAR (MYs 2003-2010 vehicles in CYs 2005-2011).

Table 7-23: Fatality Increase (%) per 100-Pound Mass Reduction While Holding Footprint Constant (2012–2016 Analyses)

Vehicle Class ⁸¹⁷	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
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.

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, though it is important to note that these best estimates are not statistically significantly different from zero. NHTSA has conducted a sensitivity analysis to illustrate the uncertainty of the estimates and has determined that inclusion of these estimates does not alter the agency’s determination of what is economically meaningful just because the effects are so small. NHTSA continues to believe it is reasonable for the analysis to continue to include the best available estimates despite their lack of statistical significance at the 0.05 level. Like past analyses, the most recent analysis uses the best-available data and estimates. NHTSA believes it is inappropriate to ignore the 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 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 5th- 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 be relatively likely that mass reduction in

⁸¹⁷ Median curb weights in the 2012 Kahane report were 3,106 pounds for cars and 4,594 pounds for truck-based LTVs. Median curb weights in the 2016 Puckett and Kindelberger report were 3,197 pounds for cars and 4,947 pounds for truck-based LTVs.

the lightest passenger cars would be less harmful, yielding a similar net impact), but also the range of net impacts 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 report, the Draft TAR, and the 2020, 2022 and 2024 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 remove the incentive for vehicle manufacturers to produce smaller footprint vehicles. In turn, NHTSA assumes 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 of 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, various studies and workshops on the impact of vehicle mass disparity on safety concludes there has been a relationship historically. The fleet simulation study, discussed in the next subchapters, further supports the existence of this relationship and assumption that this relationship will continue to exist in future vehicle designs.

Vehicle mass continues 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 percent from MYs 2004-2011 (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 percent (from 4,204 pounds to 4,462 pounds), and the average mass of LTVs increased by 10 percent (from 4,819 pounds to 5,311 pounds). Historical reasons for mass increases within vehicle classes include manufacturers discontinuing lighter models; manufacturers redesigning 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 percent (for CUVs) and 8 percent (for sedans). The principal difference between heavier vehicles, especially truck-based LTVs, and lighter vehicles, especially passenger cars, is that 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 7-2.

Equation 7-2: Final Velocity for Focal Vehicle in an Inelastic Collision

$$v_{If} = \frac{C_R m_2 (v_{2i} - v_{1i}) + m_1 v_{1i} + m_2 v_{2i}}{m_1 + m_2}$$

Where:

v_I 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.⁸¹⁸ 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 smaller effects in the intermediate groups.

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 lower 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, that may break if hit by a high-mass vehicle, resulting in a lower delta-v than may occur if the tree were hit by a lower mass vehicle that 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, peer-reviewed the 2011 Kahane report. In preparing their 2012 report (along with the 2016 Puckett and Kindelberger report and Draft TAR), Kahane also considered 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, or demographic characteristics),

⁸¹⁸ Delta-v refers to the change in velocity experienced during a crash.

uncertainty in the model results may increase. It is recognized that the light-duty vehicle fleet in the MYs 2027-2031 timeframe will be different from the MYs 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 or downsizing, comprising databases ranging from MYs 1985-2011.

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 percent. If the statistical analysis has, over the past years, been able to accommodate mass increases of this magnitude, it may also provide reasonably reliable projections of the effects of future mass reductions of approximately 10–20 percent.

7.3.4. Alternative Mass Safety Model Specifications Examined

Table 7-24 shows the principal findings and includes sampling-error confidence bounds for the five parameters the CAFE Model uses to assess the impacts of mass on safety. The confidence bounds represent the statistical uncertainty in the analysis. NHTSA’s 2011, 2012, and 2016 reports acknowledge another source of uncertainty in the mass-safety baseline statistical model, which can be varied by choosing different control variables or redefining the vehicle classes or crash types, thus producing different point estimates.

Beginning with the 2012 Kahane report, NHTSA provides results of 11 plausible alternative models. Each alternative model is 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 applies 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 7-24: Fatality Increase (%) Per 100-Pound Mass Reduction While Holding Footprint* Constant (Alternative Models)

		Cars < 3,201 Pounds	Cars ≥ 3,201 Pounds	CUVs and Minivans	LTVs† < 5,014 Pounds	LTVs† ≥ 5,014 Pounds
Baseline Estimate		1.12	0.89	-0.25	0.31	-0.61
95% Confidence Bounds (sampling error)	Lower:	-0.57	-0.09	-1.55	-0.51	-1.46
	Upper:	2.81	1.87	1.04	1.13	0.25

11 Alternative Models:					
1. Without CY control variables	-0.18	0.57	-0.58	0.35	-0.24
2. By track width and wheelbase	0.69	0.91	-0.48	-0.44	-0.90
3. Track width/wheelbase w. stopped veh data	0.76	-0.38	-0.18	-0.77	-1.91
4. Without non-significant control variables	0.90	0.67	0.14	0.36	-0.50
5. CUVs/minivans weighted by 2010 sales	1.12	0.89	-0.06	0.31	-0.61
6. With stopped-vehicle State data	1.24	-0.27	-0.08	0.21	-1.55
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	1.73	1.76	0.01	0.35	-0.74
9. Control for vehicle manufacturer	2.08	1.88	-0.01	1.12	0.30
10. Limited to good drivers‡	2.25	2.24	-0.33	0.40	-0.45
11. Control for vehicle manufacturer/nameplate	2.22	2.96	-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.

‡ Blood alcohol concentration (BAC) =0, no drugs, valid license, at most one crash and one violation during the past three 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 1.12-percent increase in societal fatality risk. The corresponding estimates for the 11 alternative models range from a 0.18-percent decrease to a 2.22-percent increase.

The tested alternative models illustrate both the fragility and the robustness of baseline estimates. The variation among NHTSA's coefficients is large relative to the baseline estimate. For cars < 3,201 pounds, the estimated coefficients range from roughly zero to 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). The estimate of societal effect of mass reduction can appreciably change when the vehicle, driver, and crash factors are varied.

The variations are not large in absolute terms. The ranges of alternative estimates are in line with the sampling-error confidence bounds for the central estimates. In the alternative models, mass reduction tends to be more harmful in lighter vehicles and more beneficial in 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 9 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 available and provides the best estimates of the impacts of differential mass reductions on safety. It is important to note that none of the mass-related

safety coefficients applied in the CAFE Model is statistically significant (*i.e.*, distinguishable from zero) at the 95-percent confidence level.

7.3.5. Fleet Simulations Model

Commenters to recent CAFE rulemakings, including some vehicle manufacturers, suggest that designs and materials of more recent model year vehicles may weaken the historical statistical relationships between mass, size, and safety. NHTSA agrees that the statistical analysis will 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 traditionally relies solely on real-world crash data as the basis for projecting the future safety implications for regulatory changes. NHTSA requires 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 vehicle fleet in the MYs 2027-2031 timeframe is different from the MYs 2004-2011 fleet analyzed in the 2012 study. This is not a new or unique phenomenon but instead reflects an inherent challenge in regulating an industry reliant on continual innovation. The statistical analysis reviewed above is NHTSA's sixth evaluation of the effects of mass reduction or downsizing, comprising databases ranging from MYs 1985-2011. Despite continual claims that modern light-weight engineering renders current data obsolete for projecting future relationships, results of the six studies, while not identical, is generally consistent in showing a small, negative safety impact related to increased mass disparity. NHTSA strongly believes that real-world crash data remains the best, most relevant data to measure the effect of mass reduction on safety.

A persistent question remains whether historical safety trends apply due to fundamental changes to light-weight vehicle design. To address this concern and to verify whether real-world crash data remains 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 that evaluate safety in a broader range of real-world representative crashes. NHTSA contracts with GWU to develop a fleet simulation model to study the relationship between light-weighted vehicle design and injuries and fatalities. The study involves simulating crashes on eight test vehicles, five of which are equipped with light-weight materials and advanced designs not yet incorporated into the U.S. fleet. The study centers on the comparison of safety performance for hypothetical light-weighted vehicle designs relative to a baseline of existing vehicles. The study assesses safety impacts of lighter newer vehicles across frontal crash types, including crashes with fixed objects and other vehicles. Other vehicles include, for example, older, lighter, heavier, and newer vehicles that represent variation in crash risks as a function of mass disparity in the vehicle fleet. This study assesses a wide range of vehicle speeds and uses mid-size male and mid-size female dummies. The model year vehicles evaluated in this study are from 10 to 20 years ago, and materials and designs have continued to evolve during that time. This raises questions about whether new materials and designs change the historical relationship between mass and safety.

The methodology focuses on frontal crashes because of the availability of existing vehicle and occupant restraint models. Representative crashes are simulated between baseline and light-weight vehicles against a range of vehicles and roadside objects using two differently sized belted-driver occupants (adult male and small female) only. No passenger(s) or unbelted-driver occupants are considered in this fleet simulation. The occupant injury risk from each simulation is calculated and summed to obtain combined occupant injury risk. The combined occupant injury risk is weighted according to the frequency of real-world occurrences to develop overall societal risk for baseline and light-weighted vehicles. The generic

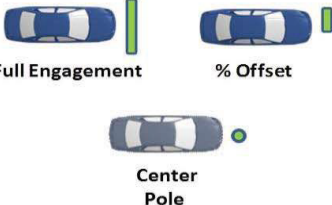
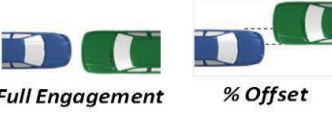
restraint system developed and used in the baseline occupant simulations is also used in the light-weighted vehicle occupant simulations as the purpose of this fleet simulation is to understand changes in societal injury risks (SIRs) because of mass reduction for different classes of vehicles in frontal crashes. No modifications to the restraint systems are made for light-weighted vehicle occupant simulations. Any modifications to restraint systems to improve occupant injury risks or SIRs in the light-weighted vehicle conflate results without identifying effects of mass reduction only. The following subchapters provide an overview of the fleet simulation study:

Eight vehicles are evaluated in the study. All light-weighted variants are designed for the study rather than real-market alternatives; thus, the light-weighted vehicles in the study differ from corresponding versions that could be feasibly produced by the original manufacturer. The following vehicles are included in the study:

- MY 2001 Ford Taurus finite element model baseline and two simple design variants include 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.
- MY 2011 Honda Accord finite element baseline vehicle and its 20-percent light-weight vehicle designed by Electricore. This mass reduction study was sponsored by NHTSA.
- MYs 2009-2010 Toyota Venza finite element baseline vehicle and two design variants included a 20 percent light-weight vehicle model (2010 Venza) funded by EPA and ICCT and a 35 percent light-weight vehicle (2009 Venza) funded by CARB.

Light-weight vehicles are designed to have similar vehicle crash pulses as baseline vehicles. More than 440 vehicle crash simulations are 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 are used as inputs in the occupant simulation models.

Figure 7-5: Vehicle Crash Simulations

Speed (mph)	Crash Partner	Crash Type Configuration	Occupant Sizes
15 20 25 30 35 40	 Fixed Object	 Full Engagement % Offset Center Pole	 Midsize Male (Target) Small Female (Target)
15 20 25 30 35	 Vehicle	 Full Engagement % Offset	 Midsize Male (Partner) Midsize Male (Target) Small Female (Partner) Small Female (Target)

For vehicle-to-vehicle impact simulations, four finite element models are chosen to represent the fleet as shown in Table 7-25. The partner vehicle models are selected to represent a range of vehicle types and weights. It is 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 are evaluated in this study.

Table 7-25: Base Vehicle Models Used in the Fleet Simulation Study

Vehicle Models		FE Weight / No. Parts /Elements	
Taurus (MYs 2000-2007)			1505 kg / 802 / 973,351
Yaris (MYs 2005-2013)			1100 kg / 917 / 1,514,068
Explorer (MYs 2002-2005)			2025 kg / 923 / 714,205
Silverado (MYs 2007-2013)			2270 kg / 719 / 963,482

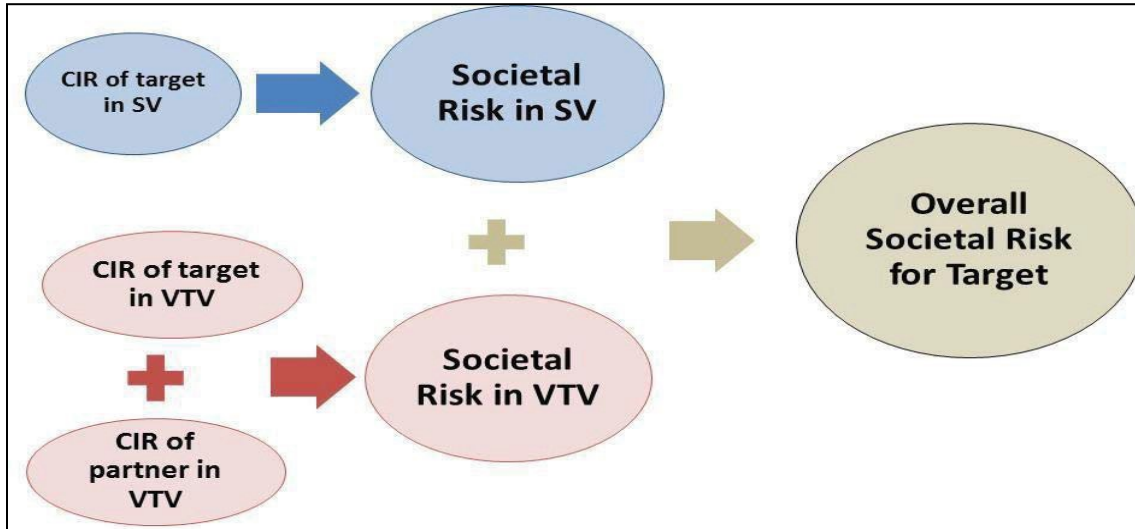
Vehicle simulations generate vehicle deformation and acceleration responses utilized to drive occupant restraint simulations. In turn these responses are used to predict the risk of injury to the head, neck, chest, and lower extremities. In all, more than 1,520 occupant restraint simulations were conducted to evaluate the risk of injury for mid-size male and small female drivers.

The SIR, as computed by Equation 7-3, for a target vehicle 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 (N_{partner}) at a given impact speed (P_{speed}), for a given driver occupant size (L_{occsz}), in the target or partner vehicle (T/P), in a given crash configuration (M_{config}), and in a single- or two-vehicle crash (K_{event}). CIR (v) represents the combined injury risk (by body region) in a single crash incident. The variable (v) designates the weighting factor (*i.e.*, percent of occurrence, derived from NASS Crashworthiness Data System) 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 7-3: 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: Diagram of Computation for Overall Change in Societal Risk



The fleet simulation is performed using 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 are simulated. The change in driver injury risk between the baseline and light-weighted vehicles provides 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, adjustments to the structural designs will 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 7-26.

In general, the SIR in the frontal crash simulation associates the small size driver is elevated in comparison to that of the mid-size driver. However, both occupant sizes have levels of injury risk in the simulated impact configurations representative of the regulatory and consumer information testing. NHTSA examines three methods for combining injuries with different body regions. One observation is that the baseline mid-size CUV model is more sensitive to leg injuries.

Table 7-26: 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 Light-weight	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 and 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 looks at light-weight designs for a mid-size sedan and a mid-size CUV and does not examine safety implications for heavier vehicles. The study also limits to only frontal crash configurations and considers just mid-size CUVs whereas the statistical regression model considers all CUVs and all crash modes.

The change in the safety risk from the MY 2010 fleet simulation study is 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 are performed only in frontal crash mode and do 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 assumes 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 undertakes 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, significantly 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

Chapter 4.1 discusses the sales response, which 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 to slower adoption of safer vehicles, while increased vehicle sales would have the opposite effect. Chapter 4, describes scrappage response, which impacts safety because it changes the rate at which older, less safe vehicles are retired from service. Collectively, sales and scrappage influence how quickly the fleet will “turn over” to newer vehicles, which tends to be safer than older vehicles. Any effects on fleet turnover caused by fuel economy and efficiency standards increase 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. 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 have a lower fatality risk than older vehicles, all else being equal. Improvements fleetwide safety in new vehicles as discussed in Chapter 7.2, resulting in an 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.

In Chapter 4.3, NHTSA describes how it anticipates lower standards will accelerate fleet turnover, which means miles that will be driven in older vehicles will instead be driven in newer vehicles. Consequently, more miles will be driven in newer vehicles with a lower fatality risk. 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.

The agency treats 90 percent of costs associated with these changes in fatality risk as private costs. This share of costs is assumed to be borne by drivers of vehicles rather than society more broadly. These costs are not offset by additional benefits since manufacturers are responsible for deciding how to design and price vehicles. The remaining 10 percent of these costs are treated as external costs.

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. Standards can 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, NHTSA uses a rebound effect of 15 percent. A full discussion of the basis for selecting this rate is provided in Chapter 4.3.3.

Rebound miles driven 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. 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 agency anticipates 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, also should act as a caution for drivers considering added crash risk exposure.

NHTSA considered several approaches to estimating internalized crash risk. One method assumes that drivers value harm to themselves as well as legal liability for causing harm to others. It considers that if all fatalities in single-vehicle crashes are fully valued, then 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, but do not value property damage incidents in multi-vehicle crashes. Based on data in Blincoe, *et al.* (2023),⁸¹⁹ multi-vehicle PDO crashes account for about 6 percent of all societal crash costs, leaving 94-percent recognized under this approach. Yet another approach would assume drivers value injury crashes, but do not account for non-injury related costs, such as property damage and traffic congestion. This approach results in roughly an 88-percent estimate of costs internalized. Acknowledging differing estimates of this proportion, NHTSA believes 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, NHTSA assumes 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 Property Damage-Only 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 and scrappage impacts. These factors are interactive, and the Model does not predict which fatalities are “only” attributable to any of the three responses; the Model 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-related and fleet-turnover-related responses.

NHTSA computes rebound safety impacts 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 7-4.

Equation 7-4: Fatalities Due to Rebound

$$Rebound_{alt} = \left[\frac{RVMT_{alt} - NRVMT_{alt}}{Veh_{Alt}} - \frac{RVMT_{base} - NRVMT_{base}}{Veh_{base}} \right] * FatalityRate_{base} * Veh_{base}$$

Where “RVMT” is VMT, including rebound miles, “NRVMT” is VMT excluding rebound miles, “Veh” is the quantity of vehicles, “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

⁸¹⁹ Blincoe L. *et al.*, The Economic and Societal Impact of Motor Vehicle Crashes, 2019 (Revised), Report No. DOT HS 813 403, NHTSA: Washington, D.C. (2023), available at: <https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/813403.pdf> (accessed: May 22, 2026).

reference baseline standards. The values will appear as zero for reference baseline standards in the outputs. The equation used to calculate fatalities due to curb weight (mass) change is as shown in Equation 7-5.

Equation 7-5: Fatalities Due to Curb Weight Change

$$\Delta CW \text{ Fatalities}_{alt} = (FatalityRate_{alt} - FatalityRate_{base}) * RVM T_{base}$$

NHTSA then computes the impacts of changing fleet turnover as the remainder.

Equation 7-6: Fatalities Due to Sales/Scrappage

$$\text{Sales and Scrap Fatalities}_{alt} = (Fatalities_{alt} - Fatalities_{base}) - \text{Rebound Fatalities}_{alt} - \Delta CW \text{ Fatalities}_{alt}$$

The same process was used to calculate non-fatal and PDO crashes with their corresponding rates.

7.7. Valuation of Safety Impacts

In the CAFE Model’s cost and benefit accounting, fatalities, non-fatal injuries, and property-damage crashes are valued as a societal cost. These values are based on the comprehensive value of a fatality, which includes the lost quality of life and is quantified in the VSL. In addition, their value is based on economic consequences, such as: medical and emergency care, insurance administrative costs, legal costs, and other economic impacts not captured in the VSL. These values were first derived from data in Blincoe *et al.* (2015) and updated in Blincoe *et al.* (2023),⁸²⁰ adjusted to 2024 values, and updated to reflect the official DOT guidance on the VSL.⁸²¹ Non-fatal injury costs, differ according to severity, are weighted according to the relative incidence of injuries across the abbreviated injury scale (AIS). To determine this incidence, the agency applies a KABCO/MAIS translator to CRSS KABCO-based injury counts from 2017 through 2019. This produces the MAIS-based injury profile. This profile is used to weigh non-fatal injury unit costs derived from Blincoe *et al.* (2023), adjusted to 2024 values and updated to reflect the official DOT guidance on the VSL. Property-damaged vehicle costs are also taken from Blincoe *et al.* (2023) and adjusted to 2024 economics. The VSL does not impact property damage. This gives societal values of \$14.1 million for each fatality, \$338,000 for each non-fatal injury, and \$9,700 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.

⁸²⁰ *Id.*

⁸²¹ Timothy, D., Departmental Guidance on Valuation of a Statistical Life in Economic Analysis, last revised: 2025, available at: <https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis> (accessed: May 22, 2026).