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Large-Scale Field Test of Forward Collision Alert And Lane Departure Warning Systems

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16. Abstract

This report covers a field study on an innovative large-scale data collection technique used to gather information about how crash avoidance systems operate in the field and how drivers respond to them. Although the specific systems studied were the General Motors (GM) camera-based forward collision alert (FCA) and lane departure warning (LDW) systems, this technique could be readily applied to other emerging active safety (crash avoidance) systems and used to better inform emerging active safety consumer metrics. It should be noted that both the FCA and LDW systems evaluated have consistently met the National Highway Traffic Safety Administration's Crash Avoidance New Car Assessment Program (CA NCAP) performance criteria since this program was initiated. The study team found that this data collection technique has several distinct strengths, including cost, sample size, drivers using their own vehicles where they can turn systems off, ability to look at long-term effects, data efficiency, and the ability to acquire "rapid-turnaround" large-scale results, and that this new data collection technique is ideally suited for understanding the safety impacts of crash avoidance systems.

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Executive Summary

This field study used an innovative large-scale data collection technique to gather information about how crash avoidance systems operate in the field and how drivers respond to them. Although the specific systems studied were the General Motors (GM) camera-based forward collision alert (FCA) and lane departure warning (LDW) systems, this technique could be readily applied to other emerging active safety systems and used to better inform emerging active safety consumer metrics. It should be noted that both the FCA and LDW systems evaluated have consistently met NHTSA's Crash Avoidance New Car Assessment Program (CA NCAP) performance criteria since this program was initiated.

The telematics-based data collection technique employed harnessed the unique and powerful telematics capabilities of OnStar coupled with a production crash avoidance module (i.e., the front camera module) that was specifically designed to support the type of active safety system data collection described in this paper focused on gathering key, high-priority numeric data. In this study, 1,958 consenting owners of model year 2013 Chevrolet Equinox, Cadillac SRX, and Cadillac XTS vehicles equipped with the FCA and LDW systems provided data on alert events and driving exposure over the course of about a year. Beyond the sheer amount of active safety system data collected, the geographic span of the data collected via this remote data collection approach was also unprecedented, as vehicles from 48 of the 50 States were represented in this effort.

Data analysis was enhanced using existing highly detailed field operational test data (e.g., forward looking video) at UMTRI. Thus, targeted, large-sample data collection, combined with information from highly detailed data, were used together to develop an efficient way to understand the performance of two active safety systems currently included in NHTSA's CA NCAP Program.

Two general types of data were collected in the current study: (1) "snapshots" of kinematic and other variables 3 to 6 seconds before, at, and 4 seconds after either FCA imminent crash or LDW alert events, and (2) histograms of driving data to provide information about exposure and normal driving. In addition, the time of braking onset after the alert (within 4 seconds of the alert) was recorded. Overall, these data were used to answer questions in several broad research categories: system availability, alert rates, driver acceptance (e.g., on/off setting choices), driver response to alerts, and driver adaptation over time.

Data analysis was enhanced by using highly detailed "traditional" field operational test data previously gathered by UMTRI, as part of the NHTSA-sponsored Advanced Collision Avoidance Study (ACAS) field operational test and Federal Highway Administration -sponsored Safety Pilot efforts. These data provided an extensive set of multi-channel video and continuously measured kinematic information, which was coupled with the current targeted, large-sample data collection, to develop an entirely new and efficient way to understand the field performance of two active safety systems. These previous FOT datasets were invaluable in developing some key algorithms to aid in understanding the data patterns observed with the more limited numeric data gathered in the present study.

Based on work conducted under the ACAS FOT, FCA imminent alerts were classified into scenarios to better understand system performance and driver behavior. We developed seven scenarios based on our determination using the available data of whether the lead vehicle (LV) stayed in path 4 seconds after the alert, the longitudinal movement state of the LV, and whether the host vehicle (HV) steered or not. The seven scenarios, as well as the estimated corresponding percentages of FCA imminent alerts observed in each of these scenarios, which total up to 100 percent, are shown below.

1. Approaching slowing vehicle (19% of alerts)
2. Approaching stopped vehicle (0.4%)
3. Approaching slower or accelerating vehicle (31%)
4. Oncoming traffic (considered out-of-path false alerts) (2%)
5. Target dropped - host changes lanes (11%)
6. Target dropped - host stays in lane (16%)
7. Target dropped - host lane unknown (20%)

These scenario classification definitions were used throughout FCA analysis to understand context surrounding FCA imminent alerts. The first two scenarios shown above are considered key scenarios for preventing rear-end crashes (though it should noted that the second "Lead Vehicle Stopped" scenario rarely occurred). The remaining scenarios can typically be resolved with minimal driver response. At a high level, observed driver responses were consistent with expected responses for these scenarios (e.g., higher decelerations were observed when approaching a slowing or stopped vehicle).

The availability of the systems were evaluated as a portion of the time the system would be expected to be available based on the LDW (above 35 mph) and FCA (above 25 mph) minimum operating speeds. LDW system availability was primarily driven by lane confidence, whereas FCA system availability above was primarily driven by the presence of a detected lead vehicle. Based on system-determined reasons for unavailability, weather and poor visibility occurred substantially less than 1 percent of the driving time.

Driver behavior surrounding alerts was investigated in several ways. The on/off setting choice can be thought of as the most fundamental and primary measure of driver acceptance, which interacted in important ways with the alert type setting. For both LDW and FCA, the Cadillac SRX and Cadillac XTS drivers had the option of choosing between warning beeps or haptic seat vibration pulses (referred to by GM as the safety alert seat), which applied to both systems.

Cadillac drivers selected the safety alert seat (over beeps) 90 percent of the time, and when the haptic seat was turned on, the LDW system off time was 38 percent. For Chevrolet Equinox drivers, who only had the beeps option, the corresponding LDW off time nearly doubled increasing to 71 percent. More generally, the LDW Off time increased until leveling off at about 10,000 miles (approximately one year of driving). At that point, drivers generally settled on whether they left the system on or off. Drivers who drove more miles per month (1 sd above the mean monthly mileage) also had over 40 percent greater odds of system deactivation. In addition, Equinox drivers who spent more time driving over the right lane boundary or who drove more in the 35- to 55 mph speed range tended to turn the system off more.

For FCA, there were four setting choices (far, medium, and near alert timing, as well as an off setting). Overall, system off time was considerably lower for FCA than LDW, and alert type impacted off time in a similar fashion. When the safety alert seat was selected (rather than beeps) by Cadillac drivers, FCA system off time was 6 percent. For Equinox drivers (who only had beeps option), the corresponding FCA off time nearly tripled to 17 percent. Together with the LDW results reported above, these results clearly suggest the safety alert seat increases driver acceptance of both LDW and FCA systems, which is further supported by the increased use of the FCA Far alert time setting for Cadillac safety alert users (72%) relative to Equinox (49%) beeps users. The Far setting was the most common setting observed across vehicles, followed by medium and then near. In general, drivers started out using the Far setting, explored other settings (generally from 5,000-25,000 miles), and then returned to the Far setting. Use of the off setting also decreased with age.

Driver response to FCA imminent alerts was measured in three ways. First, PABT was defined as the time between the alert and initial brake onset for cases where the driver's foot was on the accelerator at the time of the alert (eliminating PABTs either below 0.4 sec or above 3 seconds). Second, using these same cases, average deceleration was defined as the speed reduction between the alert and 4 seconds after the alert, divided by the 4-second time interval. A third driver response measure focused on non-response, defined as the lack of any braking occurring between 0.4 and 3 seconds after the alert. These driver response measures were evaluated as a function of odometer (experience/time) and FCA scenario, and additional analysis focused on addressing the two key FCA in-path scenarios (e.g., lead vehicle slowing or stopped), where substantially higher decelerations were observed (discussed further below).

PABT was affected by a number of factors, with FCA setting, following distance at alert, weather (wiper on/off), time of day (day/night), speed at alert, and having the most significant effects. Drivers were 0.11 s slower with the system Off compared to Far (which used the same alerting algorithm to record phantom alerts not presented to the driver). The corresponding difference was 0.07 s for the two key in-path FCA scenarios. For context, a vehicle travels about 1 foot per 10 mph in 0.07 s (e.g., 7 ft at 70 mph, 6 ft at 60 mph). Responses were about 0.13 s slower for every 10 mph increase in speed at alert and about 0.05 s slower for every 10 m increase in following distance at alert. In poor weather conditions (wipers on), responses were 0.07 s slower to all scenarios and 0.11 s slower in the two key scenarios, compared to when wipers were off. The effect did not vary by time of day (night versus day). Thus, in conditions of poorer visibility, braking responses were slower.

For driver braking (average deceleration) levels following an alert, alert scenario was the strongest predictor. Although this scenario effect interacted with both following distance and vehicle speed, in general, the two key in-path alert scenarios resulted in much greater deceleration (averaging approximately 2.0 m/s^2 or 0.20g) than the remaining scenarios (averaging below 0.5 m/s^2 or 0.05g). For these scenarios, setting was a significant predictor of average deceleration, but observed differences were a relatively small 0.2 m/s^2 between settings. Consistent with the observed PABT data, poor visibility (having the wipers on) led to stronger average decelerations (0.12 m/s^2 higher). For the lead vehicle stopped FCA scenario, every 10 mph increase in speed at alert resulted in 2.6 m/s^2 higher average deceleration levels, whereas for the LV braking scenario, every 10 mph increase in speed at alert resulted in 0.13 m/s^2 higher average deceleration levels.

Driver non-response levels are shown below for the FCA scenarios identified:

1. Approaching slowing vehicle (19%)
2. Approaching stopped vehicle (24%)
3. Approaching vehicle moving at slower (but not braking) or accelerating (54%)
4. Oncoming traffic (considered out-of-path false alerts) (66%)
5. Remaining scenarios (target lost after 4 sec) (81%)

Thus, the driver non-response levels were highest for conditions in which the lead vehicle was estimated to be not present 4 seconds after the alert, or when present but accelerating at the 4 sec post-alert time. In some cases of non-response for these two conditions, the driver may have coasted rather than braking to manage the situation.

Overall, system alert rates were higher when the system was off relative to a matched system-on condition (i.e., for LDW the On setting, for FCA the Far alert timing setting), and LDW alerts occurred markedly more often than either FCA headway or FCA imminent alerts. Median LDW alert, FCA headway alert, and FCA imminent alert rates (per 100 miles) were 29 percent, 18 percent, and 19 percent higher when the crash avoidance system was OFF rather than ON. Median LDW alert rates for the On and Off setting were 37.4 and 48.4 per 100 miles respectively. Median FCA headway alert rates for the Off, Far, Medium, and Near settings were 9.6, 8.1, 2.4, and 0.17 per 100 miles respectively. Median FCA imminent alert rates for the Off, Far, Medium, and Near settings were 1.3, 1.1, 0.75, and 0.54 per 100 miles respectively. (Note that the pattern of decreasing FCA alert rates as alert timing increases from Near to Far setting is expected based on the FCA alert timing algorithms.)

Relative to previous traditional active safety FOT efforts, one of the particular strengths of this study was the ability to look at changes in data patterns over a considerably longer period (e.g., about 1 year instead of 6 weeks) for a larger sample of drivers (e.g., 2,000 instead of 100). Overall, there was no substantial evidence of unintended consequences due to driver adaptation. As odometer (and hence time) increased, whether or not the system was turned on, alerts rates went up for LDW and down for FCA, with the FCA reduction dependent on the estimated FCA scenarios. As would be expected, oncoming vehicle (out-of-path) alert rates did not change over time, since these alerts are largely out of the driver’s control. In contrast, alerts to lead vehicles that are accelerating or stopped, and alerts where the lead vehicle was lost but the host vehicle did not change lanes or the driver’s lane position was unknown decreased the most. These could be argued to be scenarios that the driver can anticipate and perhaps can adapt to avoid setting off the FCA. In the two key in-path FCA scenarios described above (where a lead vehicle remaining present), alert rates decreased somewhat as odometer increased.

Finally, changes in normal driving behavior over time (odometer) was examined in terms of following distance and time spent over the left lane and right lane boundaries. Overall, drivers who started with more extreme following distances (short or long, relative to other drivers) or percent of time spent over either lane boundary tended to become more like an average driver over time. This suggests an effect of getting used to the vehicle rather than an effect of the system itself.

In summary, this new telematics-based, large-scale OnStar data collection technique has several distinct strengths for evaluating active safety systems, including cost, sample size, drivers using their own vehicles where they can turn systems off, ability to look at long-term effects, data efficiency, and the ability to get “rapid-turnaround” large-scale results. Since this technique currently focuses on key high-priority numeric data, it complements and benefits from the extensive set of multi-channel video and continuously measured kinematic information gathered in traditional FOTs. This new type of telematics-based data collection appears ideally suited for understanding the safety impacts of active safety (crash avoidance) systems that are rapidly emerging globally.

Introduction

In the last decade, there has been a dramatic increase in automotive production active safety systems using external-looking radar, camera, and/or ultrasonic sensors intended to help drivers avoid crashes (or reduce crash impacts), rather than protect occupants in the event of a crash. While some systems, such as electronic stability control actively intervene in vehicle control, many systems assist the driver with the vigilance task that is fundamental to safe driving. These systems present warnings to the driver when the vehicle kinematics or position meet certain criteria that could indicate a developing unsafe crash situation. Furthermore, some of these emerging active safety systems are now part of NHTSA's New Car Assessment Program. This provides further motivation to better understand system field performance to support consumer metrics.

Two such warning-based driver assistance systems are FCW and LDW. (GM refers to the former system as forward collision alert, FCA). FCA warns drivers when they closing too fast on vehicles ahead or if they are following much too closely (tailgating). LDW warns the driver when the vehicle drifts across a lane boundary without a turn signal. Both these systems are included in the NCAP program, which includes associated system performance requirements (e.g., alert timing requirements). FCW and LDW systems have been studied in multiple field operational tests such as the Advanced Crash Avoidance System study (Ervin et al., 2005) and the Safety Pilot study.

The Integrated Vehicle-Based Safety Systems (IVBSS) study involved extensive collection of data, including video and detailed kinematics, from 108 drivers of a fleet of FCA- and LDW-equipped test vehicles. Each driver drove for 6 weeks (2 weeks without the active safety systems and 4 weeks with the systems on). The study was groundbreaking in its early look at the promise of multiple integrated crash avoidance systems. For the crash-reduction analysis with IVBSS, the target crash types included rear-end collisions, lane/road departures, lane change/merge crashes, and crashes initiated by loss of control in a curve. Analysis of the conflict data showed that there were 33 percent fewer lane-change conflicts and 19 percent fewer road-departure near-events. Relating these changes in conflicts to crashes, Volpe estimated that the set of collision avoidance technologies evaluated in the IVBSS study would reduce target crash types between 6 percent and 29 percent (Nodine, Lam et al. 2011).

FOTs are relatively expensive to conduct, and thus, there are limitations on sample size and duration of testing. As each new active safety system approaches the market, it will be increasingly challenging to use the traditional FOT paradigm as the primary means of evaluation. This report describes a complementary and possibly alternative approach to collect data on such systems and drivers' behavior in response to those systems on a large scale for a more affordable cost. This approach could be used to inform decision-making with respect to active-safety-related consumer metrics and regulations, such as NCAP.

This paper describes a distinct alternative approach to a traditional FOT, but which also leverages existing traditional FOT data to aid in a more complete interpretation of data collected. This approach is designed to make use of a carefully selected set of high-priority information about alerts and normal driving behavior for a large sample of drivers of production crash avoidance system-equipped vehicles during long-term usage (approximately 1 year). Data was captured through a telematics-based (OnStar) method, and the approach traded data detail (e.g., multi-channel video gathered in traditional FOTs) for sample size, length of study, and drivers' natural behavior in their own purchased vehicles. For example, the telematics data collection approach employed in the current study did not include image or video data.

Two general types of data were collected in this study from vehicles whose owners consented to participate. Exposure-based data for each trip such as miles driven, driving time, and histograms of key variables such as speed and number of alerts, succinctly describe characteristics of each trip and provide a description of the typical driving done in each vehicle. On the other hand, alert-based snapshot data are triggered by FCA and LDW alert events. For each alert, key data elements are collected at one point in time before the alert, at the time of the alert, and after the alert. This gives three snapshots of the kinematics of the event over a large number of events. Alert-triggered data can be used to understand alert rates, driver response immediately following alerts, and changes in these measures and driver behavior over time (adaptation). In addition, alert conditions can be compared to normal driving to understand how unusual alert circumstances are in the course of normal driving.

A key element of this data-collection approach is the efficiency of the information collection, focusing only on key, high-priority data. This efficiency allows the data to be transmitted using telematics (in this case OnStar), rather than capturing it on a hard drive in the vehicle and having vehicles return to a specific location for periodic downloads (or for researchers to travel to the test vehicle). Using OnStar's unique and powerful data collection capabilities, data can be gathered remotely across a wide geographic span, and data from large samples do not take up large amounts of storage space. In the future, this method may not necessarily require OnStar or production code. Third-party telematics devices are available that could be customized, installed in drivers' vehicles, and used in place of implementing production code and OnStar. However, the third-party approach would still need an OEM's assistance, may not have access to all the key signals, and would likely be more costly because it could not take advantage of the existing scale and operations of OnStar.

Because the telematics data collection approach does not currently include image or video data, other existing datasets were used to enhance understanding of the "image-less" data analyzed in this study. For example, the Safety Pilot data (mentioned earlier) can be used to develop algorithms that link video-confirmed "ground truth" with the kinematic data available in the current study. This expands our ability to understand what the patterns in the substantially larger targeted dataset represent.

In summary, this study was designed to look at a large sample of GM FCA- and LDW-equipped production vehicles to better understand the performance of these systems in the field using a large-scale, innovative OnStar (telematics-based) data collection approach. During the course of the study, methods of analysis were developed that were tailored to analyze key high-priority data, and these methods should prove useful in similar large-scale data collection efforts. The primary focus of the study was to answer a set of research questions described in the following section.

Main Study Areas to Be Addressed

Broadly, this study was designed to address field performance of crash avoidance systems in terms of system performance, driver response and driver acceptance (e.g., On/Off system choices). To support the goals of this effort, both exposure- and alert-based data were recorded, even if the systems were turned off by the driver. (Note this latter Off option is not available to drivers in traditional FOTs).

Areas of study are divided into questions about the system and questions about the driver, but it should be noted that these are not independent.

System Behavior

System behavior in this study can be characterized as a combination of system performance, and the types of conditions the system is exposed to by real-world drivers. The types of questions about system behavior to be addressed include:

- Conditions (e.g., wipers on versus off, light/dark) under which the system is available/unavailable,
- Estimated system-false alert rates (such as no actual target present),
- Alert scenario (conditions under which alerts occur, such as vehicle speeds), and
- System performance by setting (On/Off, FCA alert timing, and alert type)

Driver Behavior

Driver behavior in this study will be assessed through histograms of exposure-based data (e.g., speed, time headway, and system setting) and through event-based data triggered by FCA imminent and LDW alerts. Note that because we do not know who is driving the vehicle, the unit of analysis will be the vehicle, not the driver. In some cases, a vehicle will be driven almost entirely by one driver, and in other cases, the vehicle will be shared. However, the anticipated limited number of drivers per vehicle and the inclusion of exposure data per vehicle allows for reasonable within-vehicle comparisons that reflect variability across the driver population. Focus areas for driver behavior questions will include alert rates, driver response after alerts, acceptance, and adaptation.

Alert Rates

Generally, alert rates in this study will be calculated as a function of miles driven. Questions about alert rates include:

- How do alert rates vary by alert setting and vehicle exposure patterns (e.g., typical speeds, following distances, and road types driven)?
- What are alert rates by scenario (e.g., For FCA, is the lead vehicle braking, stopped, moving at constant speed, or accelerating, changing lanes, or is the driver changing lanes?)
- How do alert rates vary with setting?

Driver Response After Alert

Driver response to alerts is a key element in determining system effectiveness. However, when a driver brakes or steers after an alert, we cannot determine with absolute certainty whether he/she was responding to the alert or to the situation itself. When video is available (as in traditional FOTs), it is possible at least for trained video coders to subjectively rate how surprised they feel the driver appears to be by the alert. In the current video-less data collection, if a driver is on the throttle at the time of the alert, and the response is too close to the alert time (e.g., within 400 ms), we might judge that he/she was likely not surprised by the alert. However, true driver mental state cannot be completely measured, even with video data. Consequently, in this study, we will refer to driver response time as *post-alert driver response* to make it clear that no inference is made about driver's mental state at the time of the alert, nor what cues the driver is responding to.

To more fully address driver responses to alerts, we will develop scenario definitions for the FCA imminent alert by leveraging existing FOT datasets that recorded forward-looking video and continuous numeric kinematic data. These help us understand patterns of driver behavior in response to alerts.

Broad research questions that will be investigated include:

- What is the post-alert response rate for each scenario?
- What is the distribution of post-alert response times for each scenario?
- What is the distribution of post-alert response times by setting, speed, and following distance?
- What is the distribution of post-alert driver response times for vehicles based on normal driving habits (e.g., tendency to follow more closely than other vehicles)?
- How often do drivers change lanes after an LDW?

Acceptance

Driver acceptance in this study is defined in terms of setting choices. We did not survey drivers to ask for feedback on the systems, but when drivers turn the FCA or LDW system off, this can reasonably be interpreted as indicating that the system is not deemed acceptable. (Note the factory default setting for the FCA and LDW systems system is on). For FCA, there are additional alert timing (Far, Medium, and Near) settings available that can be used to assess driver preferences (with the Far setting used as the default option).

Broad research questions that will be investigated include:

- What is the rate of use of each setting? How does this vary with interface design and driver demographics?
- How does setting choice vary with normal driving characteristics?

Adaptation

The final area of driver behavior that will be studied is potential adaptation (or change) over time associated with the systems under study. The initial request to participate in this study was sent to owners of vehicles that were as new as possible. This way, any changes in field performance can be observed within a period that starts early in vehicle ownership and ends after the approximately 1-year observation period. With a large number of vehicles (in this case approximately 2000), broad patterns of adaptation are likely to be discernable.

One challenge for this analysis is to distinguish between adaptation to a new vehicle versus adaptation to the warning systems being evaluated. However, even without a mandatory system-off baseline period (which would affect the natural behavior we are striving to observe), there are several promising avenues to making inferences about warning-specific adaptation. One is to compare patterns over time for vehicles where the system is off to those where the system is on. Another is to look at changes over time as a function of prior alert experience (e.g., total alert rate). A third avenue is to look at changes over time after a plausible grace period for vehicle adaptation (e.g., 1-2 months). Finally, changes in response to alerts themselves (e.g., post-alert response time) is more likely to represent adaptation to the alert system than adaptation to the vehicle.

Questions about adaptation that will be addressed include:

- How does post-alert driver response to FCA imminent alerts change over time? Does this vary with prior alert experience?
- How does normal driving change over time (e.g., the distribution of headway and lane-keeping behavior)? Does this vary with prior alert experience?
- Do drivers turn the system off or change settings over time?

Methods

General Approach

This study makes use of the unique telematic capability of GM's OnStar-equipped vehicles to capture data on production vehicles from consenting owners and send it wirelessly from remote locations across virtually the entire United States. Although the amount of data that can be captured from any one trip is limited relative to the extensive set of video and numeric data gathered in traditional FOTs, the ease of high-priority data capture allows massive samples to be collected relatively affordably in a rapid-turnaround manner. The data collected in the current effort were targeted towards understanding FCA and LDW field performance. General trip-level statistics and alert-triggered event data were captured from nearly 2,000 vehicle owner volunteers (distributed across 48 of 50 States) over the course of approximately 1 year of their normal driving. The data were analyzed with some reference to other FOT datasets available at UMTRI, including the ACAS FOT study and the Safety Pilot study, to augment and further develop the data analysis and interpretation. The followings sections provides details on the study methods.

Participants

Study participants were recruited by e-mail from a list of OnStar subscribers to the Onboard Vehicle Diagnostics (OVD) service who were model year 2013 owners of either a Chevrolet Equinox, Cadillac XTS, or Cadillac SRX equipped with the systems evaluated in the current study. Efforts were made to include recently purchased vehicles as close as possible to the start of data collection. Consenting participants gave permission for OnStar to capture key data from advanced vehicle technologies and provide de-identified data to UMTRI for analysis. Participants received 6 months free OnStar services in exchange for their participation. As described below, the data collection occurred automatically, without any further action on the part of the participants (e.g., taking their vehicle to have data downloaded or acquisition systems installed).

At the time the vehicle owners agreed to participate in the study, they were asked to provide information on the primary driver age, primary driver gender, and the percentage of time that they felt the primary driver drove the vehicle. This was the only personal information included in the dataset, which was associated with a random vehicle identification number as part of the de-identified dataset provided to UMTRI for analysis.

Systems and Interfaces

Forward Collision Warning

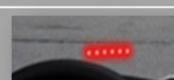
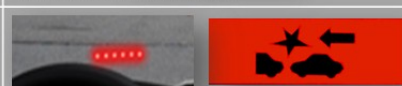
The FCA system is intended to help the driver avoid or reduce the harm caused by rear-end crashes. The GM camera-based FCA production system used a single forward-looking camera sensor, located on the windshield ahead of the rearview mirror. (The reader is referred to Raphael et al. [2011] for a discussion of the development of a camera-based FCA system.) When driving in a forward gear, the system detects vehicles directly ahead that the driver is following and that are in the projected path of the vehicle. The system detects vehicles within a distance of approximately 60 m (197 feet), and operates at speeds above 25 mph.

The key differences in the FCA system alerting approach for the three GM vehicles tested are summarized in Table 1. When the system detects a vehicle ahead, a green FCA system icon is lit to indicate the system is capable of providing FCA system alerts. When the driver's vehicle is detected to be following a vehicle ahead much too closely, this icon turns amber to indicate a Tailgating Alert condition. When the driver's vehicle is detected to be approaching a vehicle ahead too quickly, FCA provides a red flashing imminent Collision Alert either on the windshield or a high-mounted display. Additionally, eight rapid high-pitched beeps are presented from the front speakers, or if equipped with the safety alert seat (haptic seat) feature, five vibration pulses occur on both sides of the driver's seat bottom.

As indicated in Table 1, in 2 of the 3 vehicles tested, the drivers could select the crash avoidance system (non-visual) alert type to be either beeps or safety alert seat via a vehicle customization menu. This Alert Type setting is used for both the FCA and LDW systems evaluated (described below). In vehicles equipped with the safety alert seat, the factory default setting for the alert type was safety alert seat.

The FCA control is located on the steering wheel, which allows the driver to set the FCA timing to Far, Medium, or Near, or to turn the system Off." The factory default setting for FCA timing was Far." The FCA timing setting affected the timing of both the Tailgating Alert and Collision Alerts, and remained until it is was changed by the driver. Finally, it should be noted that the system evaluated did not provide automatic braking, such as that provided by some front automatic braking (or crash imminent braking) production systems.

Table 1 Forward Collision Alert Interface Design for Three Vehicles Studied

Vehicle	FCA Vehicle Ahead / Tailgating Alert	FCA Imminent Collision Visual Alert (flashing)	FCA Imminent Collision Non-Visual Alert
Equinox	 High-Head Down Display	 High-Head Down Display	Front Beeps
SRX	 Instrument Panel	 LED Windshield Display	 Safety Alert Seat (pulses on both sides) or Front Beeps
XTS	 Instrument Panel and (if equipped) Head-Up Display	 LED Windshield Display or (if equipped) Head-Up Display	 Safety Alert Seat (pulses on both sides) or Front Beeps

Lane-Departure Warning

The LDW system is intended to help drivers avoid crashes due to unintentional lane departures. The GM production system used the same camera sensor used for the FCA system described above. The system detects lane markings and operates at speeds above 35 mph.

The key differences in the LDW system alerting approach for the three GM vehicles tested are summarized in Table 2. When the system detects either a left or right lane marking ahead, a green LDW system icon is lit to indicate the system is capable of providing a lane departure warning alert toward the detected lane marking. If the vehicle drifts across a detected lane marking without using a turn signal in that direction, this icon turns amber and flashes. Additionally, depending on the lane departure direction, three left- or right-side low-pitched beeps are presented, or if equipped (and selected by the driver), the safety alert seat will pulse three times on the left or right side of the driver's seat bottom. The LDW control allows the driver to set the LDW system to On or Off. The factory default for LDW setting was On. This setting remained until it is was changed by the driver. Finally, it should be noted that the system evaluated did not provide automatic lateral control or steering wheel "nudge" cues, such as that provided by some production lane-keeping or lane keep assist production systems.

Table 2 LDW System Alerting Approach for GM Vehicles Studied

Vehicle	LDW "Ready to Assist" (lanes detected)	LDW Visual Alert (flashing)	LDW Non-Visual Alert
Equinox	  High-Head Down Display	 High-Head Down Display	Left / Right Beeps
SRX	 Instrument Panel	 Instrument Panel	 Left / Right Beeps or Seat Pulses
XTS	 Instrument Panel and (if equipped) Head-Up Display	 Instrument Panel and (if equipped) Head-Up Display	 Left / Right Beeps or Seat Pulses

Data Collection

The LDW and FCA warnings are generated by the front camera module (FCM), which both use the same forward-looking camera. The FCM accumulates and stores into its memory a pre-determined set of data during an ignition cycle. The data elements are described in the next subsection and appendix. When an ignition-on event occurs, the previous ignition cycle's data are deleted.

For the consenting vehicle owners in this study, OnStar remotely loaded a custom script onto the onboard OnStar module to retrieve the data from the FCM after ignition-off. This data is then sent over the air through the OnStar system during an ignition-off state. The OnStar back office transforms the data into a de-identified form that can be transmitted and analyzed by UMTRI. De-identification included the removal of Vehicle Identification Number (VIN) information and assignment of an anonymous vehicle index (or identification) number that remained consistent throughout the study. UMTRI received files on a daily basis during data collection and was able to parse the data and convert it into engineering units with the support of GM and OnStar experts. If connection to the vehicle failed, the module would attempt to retrieve data upon the next ignition cycle.

Under some circumstances, such as a very short interval between key off and next key on or a failure of cell service, data were not transferred. However, timestamps and ID numbers on the records allowed us to identify data gaps.

Data collection started on September 29, 2013, and continued until October 3, 2014. During the second six months of the study, it was possible that the OVD subscription could run out (even with the 6 months free OnStar offer) and not be renewed, leading to drop-out of some vehicles. However, most vehicles provided a full year of data.

Data

Because the memory available on the FCM is necessarily very limited, the data collection was designed to be efficient and targeted at gathering high-priority data to understand FCA and LDW field performance. As discussed above, data fell into two categories: exposure-based, trip-aggregated statistics data, and event-based, alert-triggered data. Trip-aggregated statistics were designed to provide basic information about a trip in the form of histograms. Alert-triggered data was triggered by either an LDW alert or FCA collision (imminent) alert; with more detailed data gathered 3- to 6 sec before the alert (specific time is known), at the alert, and 4 sec after these alerts.

Trip Aggregated Statistics

Trip aggregated statistics, also called "counter data," consisted of a trip descriptors and histograms that were designed to capture key information about each trip. These were used to understand a vehicle's exposure to various driving conditions. Key trip descriptors and histograms included the following.

- Trip time, trip distance, odometer, number of FCA events, and number of LDW total events
- Histograms (binned trip-level statistics):
    - Speed
    - Speed x Following a Vehicle Ahead (yes/no)
    - When following, Speed x Range
    - Wiper x Speed
    - Speed x Left/Right Lane Confidence
    - Lane Position
    - Trip-seconds x Setting
    - Speed x Headway (or Tailgating) Alert
    - Driver Settings for LDW (on/off) and FCA settings (far/medium/near/off)
    - Speed x Not-Ready-to-Assist (NRTA) for FCA
    - Speed x Not-Ready-to-Assist (NRTA) for LDW

Alert-Triggered Data

Alert-triggered data, in contrast, consisted of a series of signals, collected at each of three time points relative to a FCA imminent alert or LDW alert, as illustrated in Figure 1. Data was collected using two 3-second buffers, in which new signals replaced the "old" ones every 3 seconds. At alert onset, the contents of the older of the two buffers was captured, resulting in pre-event data that were collected at a known time between 3 and 6 sec before the alert. Data were also captured at the time of the alert and at 4 seconds after the alert. Finally, a counter was incremented every 50 msec throughout the trip. The value of that timer was captured at each of the three alert-triggered time points, in order to know the time within the trip of the event, as well as at the time at which initial brake travel was achieved. The timing of a brake onset that occurred within 4 seconds *after* the alert could be measured to within 50 msec. Absolute time is collected at the start of the trip, so that the time of day of the event is known.

Figure 1. Illustration of alert-triggered data collection timeline.

The alert-triggered data contained information describing the driving conditions at the three time points around the alert time. These included vehicle kinematics for both the host (driver's) vehicle and lead vehicle, system state, road geometry, and driver response. Table 3 shows a list of the key signals from the alert-triggered data (see Appendix A for a complete list of signals used to support the analysis reported in the paper).

Table 3 Key data signals for alert-triggered data

Signal collected	Sampling time relative to alert
Time into trip	Pre, at Alert, & Post
FCA state (alert or not)	Pre, at Alert, & Post
LDW state (alert or not)	Pre, at Alert, & Post
Vehicle speed	Pre, at Alert, & Post
Accelerator position	Pre, at Alert, & Post
Lateral acceleration	Pre, at Alert, & Post
Yaw rate	Pre, at Alert, & Post
Driver brake switch (initial braking onset flag)	Pre, at Alert
Driver brake pedal position	Pre, at Alert
Turn signal status	Pre, at Alert, & Post
Range to target	Pre, at Alert, & Post
Target vehicle speed	Pre, at Alert, & Post
Lane position	Pre, at Alert, & Post
Lane tracking confidence	Pre, at Alert, & Post
GPS data (time, position)	At Alert & Post
Wiper state	At Alert
Brake activation time and max pedal travel	During 4 s period after Alert

Assigning Time of Day, Sun Elevation, and Road Type Using Maps

To support analyses of system performance that considers time of day and the type of roadway, the GPS data associated with driver alert events were post-processed along with spatial information of time zones and road networks. This was necessary to determine the local time and road type classification surrounding alert events. For local time determination, the GPS data (which includes an absolute time stamp) associated with alerts is used, along with any necessary corrections for time zone and Daylights Savings Time (DST). These corrections are done using geographic information system (GIS) tools and polygons that represent the two corrections. Likewise, in order to determine road type, the GPS data associated with alert events are combined with digital maps to assign a road type attribute. As described further below, while this method of time zone assignment worked nearly perfectly, the method of road type assignment was successful approximately 75- to 80 percent of the time. After assigning time of day and road-type attributes to the alert events, GPS coordinates were removed from the dataset.

Local Time of Day

To determine the time at which alerts occurred, the latitude and longitude associated with the alerts are overlaid on a set of National Institute of Standards and Technology (NIST) geospatial polygons that represent time zones (including regions with or without DST) in the United States. However, the NIST polygons do not include bridges and causeways that are at the edges of these time zones (e.g., bridges to barrier islands or other roadways close to coasts). Therefore, the time zones for alerts in these areas and other unrepresented areas are difficult to determine. The left side of Figure 2 shows yellow points for such cases of “misses” when alert time could not be determined. UMTRI therefore expanded each time zone to capture these areas with bridge and causeways structures. The lighter colored section on the right side of the figure illustrates the expansion of the time zone polygon and the resulting matches that occur (now in green). With this adjustment to the polygons, the local time of day was computed for over 99 percent of the alert events.

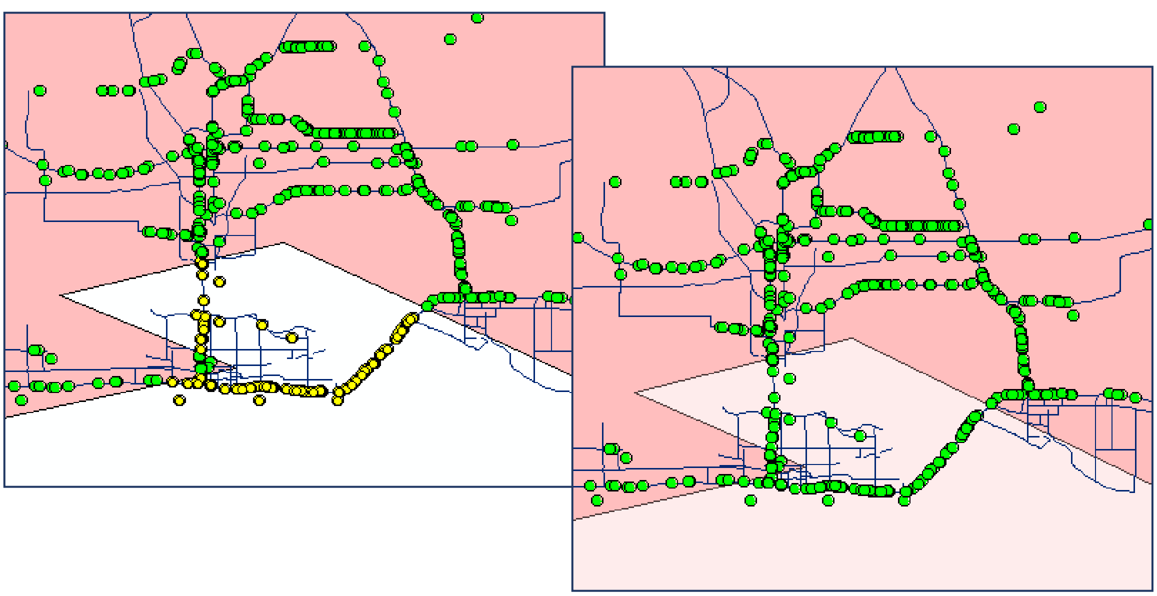


Figure 2. Overlaying GPS points of alert events before (left) and after modification (right) of NIST time zone polygons in a coastal area.

Sun Elevation Using Maps

Sun elevation is an indicator of outdoor natural illumination level. Sun elevation is the angle between the sun and the point on the horizon closest to the sun, so that it has a value of zero at sunrise and sunset, positive values during the daytime, and negative values during night. This variable is computed from latitude, longitude, and time of day and does not depend on the weather or the heading of the vehicle. Sun elevation is collected only at alerts and at end of trip. Thus, for analyses of usage and settings, sun elevation at end of trip is used because some trips have no alerts and therefore no measures of sun elevation during the trip.

Road Type Using Maps

Road types are assigned to alert events when there is confidence in matching the GPS location with a digital roadway network map. Road type is defined using the Federal Highway Administration's functional class definitions that are associated with the 2011 Highway Performance Monitoring System (HPMS) database. HPMS is a digital map that represents a subset of the national roadways, including the geometry of the road centerline and a variety of roadway attributes such as road functional class (i.e., road type). The HPMS is FHWA's source for various attributes, extent, condition, performance, use, and operating characteristics of the national roadway network. The road types (functional classes) are shown in Table 4 below. (The "local" road type was discarded from the map-matching analysis because of the small number of national highway system roads that are classified at this level.)

Table 4 Road types from FHWA's functional classification scheme for 2011

Code	**Description**
1	Interstate
2	Principal Arterial - Other Freeways and Expressways
3	Principal Arterial - Other
4	Minor Arterial
5	Major Collector
6	Minor Collector
7	Local

The process to match the alert event locations involved overlaying the GPS latitude and longitude on the HPMS. Since neither the GPS data nor the HPMS geometrics are perfect, a buffer zone was created around roadway centerlines to model the drivable area of roads using estimates of the width of different road classifications and an assumed typical GPS error. Next, the GPS points were overlaid to determine whether the points fell within the buffer distance of a roadway in the HPMS database. Those points that fell within the buffered area were considered matches, or "hits," and those that did not were considered to be points that were not matched to a road (i.e., misses). Additional heuristics were used to improve the fraction of points that were matched. This method was able to assign road type to about 75- to 80 percent of the alert events.

Figure 3 below illustrates a typical result of the matching process near O'Hare Airport near Chicago. The "hits" are small green circles and align with the HPMS digital map, while the red "X" marks "misses." These are associated with parking lots (lower left) or lower-level roads that are not included in the HPMS.

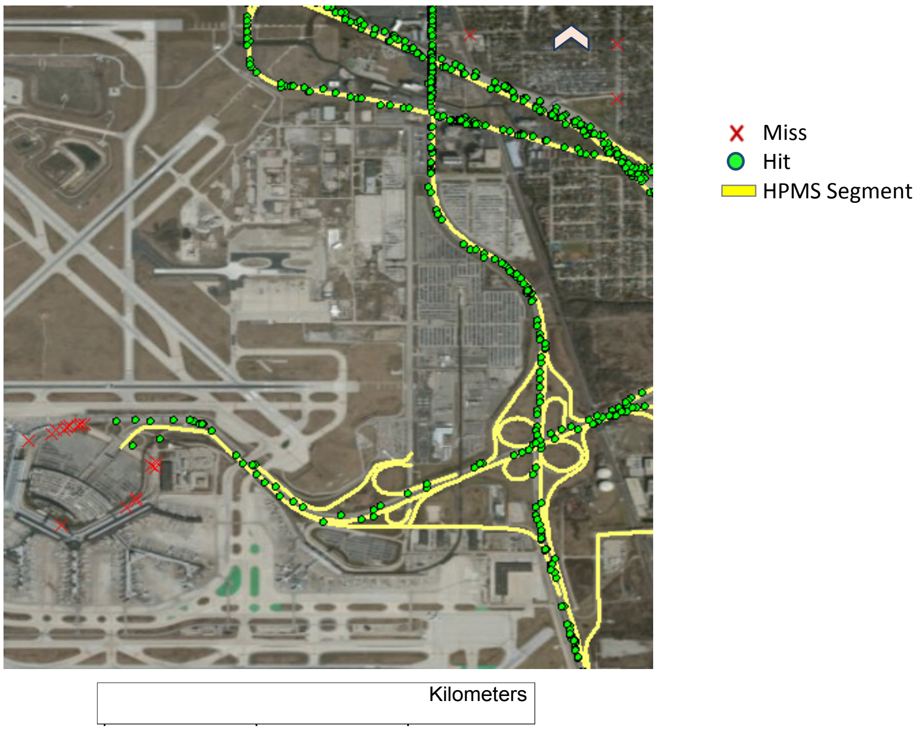


Figure 3. Alert Event Road Type Determination of "Hits" and "Misses" shown in the area around Chicago's O'Hare Airport

Data Validation

Unexpected Data Issues

The data collection capability of the production FCM was designed and implemented before the start of this study. Thus, the data collected could not be changed or corrected during the course of this study. Of the parsed data, a few expected variables were unavailable or in error. Workarounds were found for some of them, and these are described in Appendix A. If no workaround was found, the data were not used.

One missing data element was FCA reason for Not-Ready-To-Assist (NRTA). Thus, for FCA, we could identify whether the system was ready to assist or not, but could not identify the reason. Another key piece of missing information was that related to lateral movement surrounding alerts, of particular importance for understanding driver response to LDW warnings. Unfortunately, yaw rate and lateral acceleration were both unavailable. However, we were able to use position in lane to estimate whether a lane change had occurred surrounding a LDW alert. The lane change algorithm and its use in data analysis are described in the results section. Finally, there was an error in some of the bits recording relative speed, as described in Appendix A.

Ground Truth Testing

The findings in this report reflect the results of active safety systems installed in production vehicles by the manufacturer, which therefore have been exhaustively validated and tested to understand all performance, robustness, and durability characteristics of the systems studied. By design, production level systems are intended to be mature, vetted, and thoroughly and stringently screened for accuracy at all levels of design and manufacturing to ensure that performance meets or exceeds system requirements. It should be stressed that the new, innovative techniques implemented to support this research were carefully implemented using "add-on" techniques and structures to ensure their complete independence from production systems performance.

Some ground truth testing was also conducted to verify key data signals and the robustness of this new data collection and archive process. Tests were used to verify the following.

- All trip level exposure and time measures were being logged properly in the external object control module (EOCM) and OnStar module at the beginning and end of each ignition cycle.
- All trip level counters (histograms) were being properly logged in the EOCM.
- All pre-event, event, and post-event alert measures from the FCA, LDW, and associated vehicle systems were being properly logged in the EOCM when triggered.
- All EOCM logged data were transferred to the OnStar module system upon ignition off.
- All OnStar buffers were completely uploaded to the OnStar backhaul servers using customized scripts executed onboard the vehicle at the end of each trip.
- Data captured by OnStar were completely transferred to UMTRI.
- UMTRI algorithms properly parsed the OnStar data into correct engineering units.
- UMTRI database population algorithms performed as expected.

The ground truth and data verification tests were conducted at the GM Milford Proving Ground (MPG) in Milford, Michigan. A total of 24 different test scenarios were conducted, focused primarily on FCA in-path conflicts, with three repeat runs of each test conducted for statistical robustness purposes. The general test categories included (number of initial conditions shown in parentheses):

- Stopped Lead Vehicle (3),
- Constant Closing Speed on a Lead Vehicle (6),
- Lead Vehicle Slowing From a Constant Range (12), and
- Cut-in by a Slower Lead Vehicle (3).

For all tests the "truth" was measured using a portable Vehicle-to-Vehicle (V2V) wireless system mounted in both the host (following) and lead vehicle. For these tests, the V2V technology exchanged basic GPS time, rate and position data between the two radios at a nominal rate of 7.5 Hz. In addition to equipping the host vehicle with V2V, a smart phone, mounted on the windshield, was used to capture a picture of the forward scene and GPS information at the time of the FCA event. Figure 4 shows a picture from the phone, taken at the time of the FCA, for one run of a stopped lead vehicle test at 45 mph.

Figure 4. Picture of a 45 mph stopped lead vehicle test at the time of the FCA

After each test (consisting of 3 runs), the host vehicle driver performed an ignition-off event for at least three minutes. This caused scripts residing in the OnStar system to execute and perform the necessary steps of moving the logged data for that trip and the FCA/LDW alert events to the OnStar backhaul servers. A remotely located OnStar engineer than ran additional scripts to extract these data from the OnStar database and populate files which were then immediately e-mailed to an UMTRI data analyst who parsed the files and populated various tables within the UMTRI OnStar database. Next, the UMTRI analyst ran a query on these tables to summarize all the measures from the tests, which were sent in a spreadsheet via e-mail to engineers conducting the tests at the track. The test engineers then reviewed the results for overall general accuracy before conducting more tests. Overall, 129 individual runs were conducted as part of this ground truth testing.

Following the tests and after the V2V data was post-processed, UMTRI engineers then synchronized the results reported via OnStar with the continuous measures produced by the V2V system. An example plot of the synchronized results is shown below in Figure 5. The figure shows a plot of speed (upper) and range (lower) as function of time for a constant closing speed test where the host vehicle is traveling at 60 mph and approaches a lead vehicle traveling at 50 mph. In the figure, the V2V results are shown as continuous measures, while the OnStar results are single values taken at an instant in time. This figure compares the OnStar estimated speed and range at the pre-event, event, and post-event times overlaid on the same measures from the V2V system. In this example, the agreement of the measures from the two independent systems is reasonable given the overall resolution of the plots themselves.

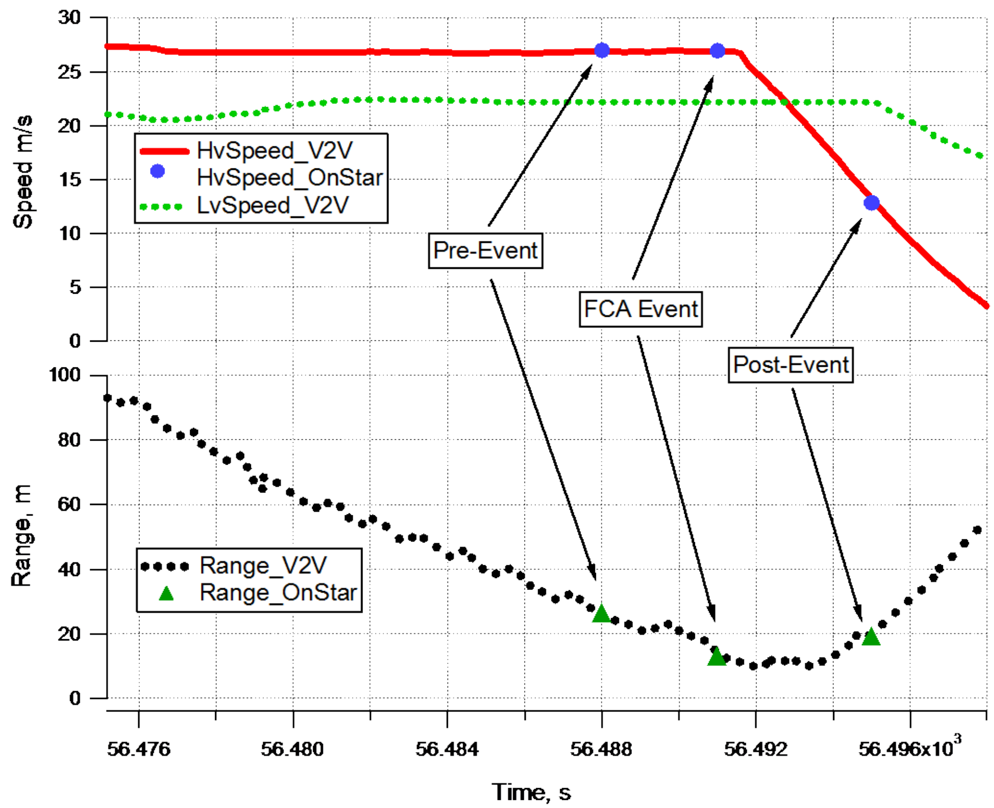


Figure 5. Time series plot showing measured (V2V) and OnStar reported data for a single ground truth run

The results of these tests showed that at the time of the alert event the average difference between OnStar and V2V reported host speed was 0.18 mph (with a standard deviation of 0.73 mph). The corresponding average range difference was -2.2 m (with a standard deviation of 2.35 m), and corresponding average range-rate difference was 0.7 m/s (with a standard deviation if 0.9 m/s). In general, the OnStar reported range values tended to be slightly greater than the V2V reported range, while the OnStar range-rate values showed a slightly higher closing rate.

Analysis Approach

The Results section describes the specific statistical and descriptive approaches used to answer each research question. These analyses generally followed the data analysis plan (Flannagan, LeBlanc, & Kiefer, 2013) that was delivered as part of the project. Appendix A provides details on the statistical modeling approaches uses to address each research question. Depending on the exact nature of the question, analysis was done at the vehicle, trip, or alert level. Statistical models were developed using either SAS 9.4 or R statistical software packages.

As mentioned earlier, a key aid for broadening the use and understanding of the current dataset involved developing algorithms using more detailed (including video) data previously gathered by UMTRI in the ACAS FOT and SP efforts. Specifically, the ACAS FOT, which studied an FCA system, included detailed assessment of the scenarios for alerts, the rate at which these scenarios occurred, and driver's subjective impressions of those alerts. In addition, the data-capture protocol for the present study (i.e., alert-triggered data at 3- to 6 seconds before, at, and 4 seconds after alert event) could be replicated for these earlier ACAS FOT data. This allowed for a direct comparison of scenario definitions using the OnStar protocol (present study) and the ones assigned in ACAS using the synchronized video and extensive set of continuous numeric data available.

In the SP effort, vehicles were equipped with a forward-looking aftermarket Mobileye camera system that can be thought of, at least at a high level, generally representative of the production camera sensor used in the present study. Thus, the measurement of range and range-rate used could be compared in the SP versus the current effort. False detection of targets could also be compared because the video gathered in the SP effort allowed for verification of target presence. Since the SP drivers did not experience alerts, their data could not be used to look at driver response, but plausible alert algorithms could be implemented and compared to data from the current study.

Before the results are presented, it should be stressed that although each of the three MY 2013 vehicles used in the current study used the same camera-based sensor, relatively small differences in the FCA and LDW alert timing experienced by the driver may exist across vehicles due to differences in vehicle-related factors such as vehicle electrical architectures, system software versions, system delays, and HMI interface delays. Hence, the reader is cautioned that any vehicle model or vehicle-model-related (e.g., HMI) effects reported in this analysis, or where these effects interacting with other variables (e.g., whether FCW or LDW system was on or off) in this analysis, could be partly due or fully explained by these differences. This caveat is particularly true if the observed differences across models are small in magnitude.

Results

The results are organized as follows. First, we present descriptive statistics on vehicles, trips, and FCA and LDW alerts. Second, we present algorithms that were developed from ACAS and SP data to deepen and broaden the analysis (e.g., FCA scenario classification of alerts). Finally, we present further statistical analysis of questions addressing for both FCA and LDW: (1) system performance, (2) alert rates, (3) driver response after alerts, (4) acceptance (e.g., on/off settings), and (5) adaptation over time.

Descriptive Statistics

Table 5 shows the distribution of vehicle make-models in the sample. Although participants were recruited across the three vehicle types and opt-in was not limited within a vehicle type, the representation of each vehicle was nearly equal. Demographic information was not obtained for 8 vehicles.

Table 5 Sample counts by vehicle make-model

Vehicle	**Sample Size**	**Percent of Sample**
MY 13 Cadillac XTS	619	32%
MY 13 Cadillac SRX	659	34%
MY 13 Chevrolet Equinox	672	34%
Vehicles with missing demographic info	8	0.5%
Total	1,958	

Table 6 shows the distribution of the primary-driver age groups, and Table 7 shows the distribution of primary-driver gender. Ages 60 to 79 made up the largest group, followed by ages 40 to 59. The gender distribution is close to even, with a slightly larger number of females compared to male primary drivers. Figure 6 shows the distributions of age groups for males and females separately. Females tend to be over-represented in older age groups compared to males.

Table 6 Sample counts by age group of primary driver

Age Group of Primary Driver (years)	Number of Vehicles	Percent of Sample
<40	143	7.3%
40-59	601	30.7%
60-79	1,078	55.1%
80+	128	6.5%
Unknown	8	0.4%

Table 7 Sample counts by gender of primary driver

Gender of Primary Driver	Number of Vehicles	Percent of Sample
Male	930	47%
Female	1,020	52%
Unknown	8	0.4%

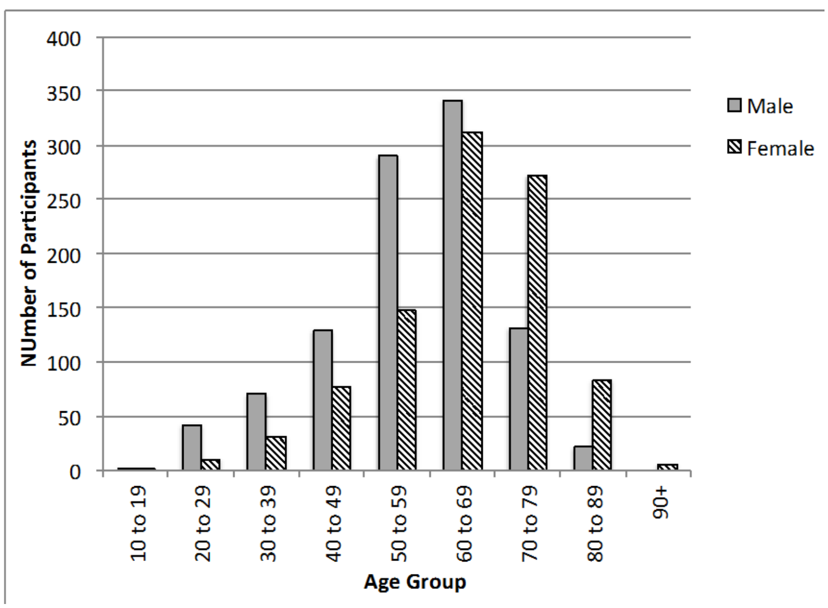


Figure 6. Number of participants in each age group, broken down by gender.

Figure 7 shows the number of vehicles enrolled in each State, and provides evidence of the geographic span advantage associated with this OnStar data collection technique. Only Montana and the District of Columbia have no residents in the sample.

Figure 7. Distribution of primary-driver home State.

Table 8 provides high-level descriptive statistics for the sample of vehicles, trips, and alerts. Note that the table includes alerts that, although recorded, were not presented to the driver because the system was turned off.

Table 8 Descriptive statistics for sample

Total Vehicles	1,958
Total Trips	2,463,142
Total Miles of Driving	18,815,458
Total Hours of Driving	615,054
Total LDW Alerts	10,058,567
Total FCA Tailgating Alerts	1,830,501
Total FCA Imminent Alerts	260,756

Table 9 shows descriptive statistics for statistics for starting and ending odometer, miles traveled, and trip durations. For example, half the vehicles began the study with an odometer of 2,368 miles or less. Vehicles traveled an average of 10,848 miles during the course of the study. A typical (median) trip (defined as an ignition cycle) lasted 9.5 minutes, whereas a 95th percentile trip length was 46 minutes. Of the 1,958 vehicles in the study, 794 (40%) were observed for 365 days (measured from the first to last data observation); 75 percent were observed for 11 months or more, and 95 percent were observed for 7 months or more.

Table 9 Mean, median, 5th and 95th percentiles of vehicle statistics

Statistic	Mean	Median	5th Percentile	95th Percentile
Starting Odometer (miles per vehicle)	3,206	2,368	613	8,247
Ending Odometer (miles per vehicle)	14,054	13,048	4,825	26,616
Total Miles Driven In Study (per vehicle)	10,848	10,046	3,250	21,263
Ave. Trip Duration (min)	15.0	9.5	0.7	46.2

Table 10, Table 11, and Table 12 provide descriptive statistics for the number of miles between alerts as well as alert rates per 100 miles (shown in corresponding parenthesis) for LDW, FCA headway (tailgating), and FCA imminent alerts for each FCA setting. (The reader is reminded that alerts are recorded in the Off setting, even though these alerts were not presented to the driver). The rates are computed for each vehicle across the study period, so the 5th and 95th percentiles are among vehicles. There were 8 vehicles that had no FCA tailgating alerts and 2 vehicles that had no FCA imminent alerts, and these were excluded from the calculation (since miles between alerts is infinite).

For LDW, the alert rate for the Off setting is generally higher than for the On setting, with median LDW alert rates (per 100 miles) increased by 29 percent. For FCA imminent alerts, the Off setting uses the same alert timing algorithm as the Far setting, and the alert rate appears higher for those who turn the system Off, with median alert rates (per 100 miles) increased by 19 percent. The Near and Medium alert timing algorithms are different, and thus cannot be compared directly to the Far and Off settings. As expected, based on the alert timing algorithms, the Near setting results in the fewest FCA imminent alerts per mile and Medium setting is between Near and Far with respect to imminent alert rates.

For FCA headway alerts, once again, the Off setting uses the same algorithm as the Far setting, and the headway alert rate appears somewhat higher for those who turn the system Off, with median alert rates (per 100 miles) increased by 18 percent. Once again, the Near and Medium headway alert timing algorithms are different, and thus cannot be compared directly to the Far and Off settings. As expected based on the alert timing algorithms, the Near setting results in the fewest headway alerts per mile and Medium setting is between Near and Far with respect to headway alerts rates.

As can be seen by comparing results across Table 11 and Table 12, for the Medium and Far FCA settings, headway alerts occur more frequently than imminent alerts. In sharp contrast, for the Near setting, headway alerts occur considerably less often than imminent alerts.

Table 10 Mean, median, 5th and 95th percentiles of miles between LDW alerts (alerts per 100 miles in parentheses) by setting

LDW Setting	Mean	Median	5th	95th
On	3.5 (44.3)	2.7 (37.4)	0.87	6.59
Off	2.8 (55.1)	2.1 (48.4)	1.00	8.65

Table 11 Mean, median, 5th and 95th percentiles of miles between FCA headway alerts (alerts per 100 miles in parentheses) by setting

FCA Setting	Mean	Median	5th	95th
Near	1101.6 (1.1)	574.1 (0.2)	48.5	3655.1
Medium	91.8 (3.8)	42.2 (2.4)	7.9	290.8
Far	20.4 (11.4)	12.3 (8.1)	3.0	60.1
Off (compare to Far)	19.3 (13.7)	10.5 (9.6)	2.5	65.9

Table 12 Mean, median, 5th and 95th percentiles of miles between FCA imminent alerts (alerts per 100 miles in parentheses) by setting

FCA Setting	Mean	Median	5th	95th
Near	322.0 (1.4)	184.5 (0.5)	32.1	1033.4
Medium	239.6 (1.2)	132.9 (0.8)	27.2	739.3
Far	145.6 (1.7)	91.6 (1.1)	19.5	443.3
Off (compare to Far)	135.6 (2.3)	77.2 (1.3)	17.1	370.7

Algorithms to Aid Analysis

Identifying Lane Changes versus Returning to Lane

Immediately following either a LDW or FCA imminent alert event, the driver might return to his/her lane (after a lane departure) or execute a lane change. (Note FCA imminent alert responses have been shown typically to not involve lateral movement). Since maximum/minimum yaw rate and lateral acceleration were not available for analysis, a workaround was developed that involved using lane position to estimate whether or not the vehicle completed a lane change within 4 seconds following an alert.

The basis for this lane change detection algorithm is illustrated in Figure 8, with further details provided in Appendix B. Figure 8 shows the absolute value of the difference in left-lane-boundary offset at event and 4 sec after event. The data shown come from UMTRI's Safety Pilot Model Deployment effort, and in this case, events are defined using lane excursions. However, similar results were found using an FCA algorithm. The figure shows that the distribution of the difference in left-lane offset is quite different for lane changes versus cases when the vehicle returns to the original lane of travel. The lane change detection algorithm that was employed assigned lane changes only to those events where the difference was greater than 0.5 m (or 20 inches; shows by the black vertical line) between the time of the alert event and 4 sec after this event.

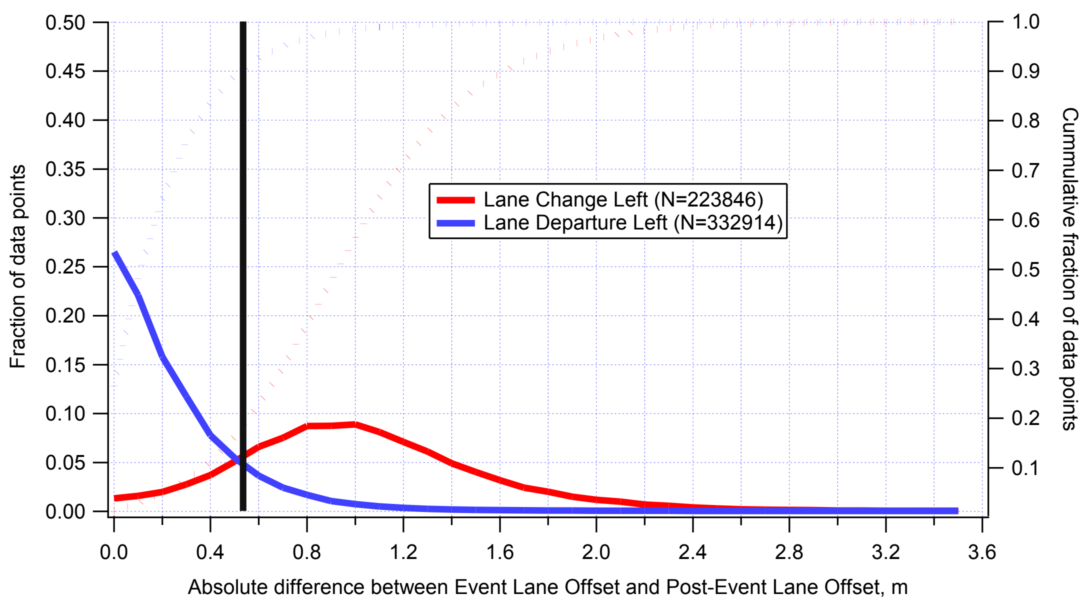


Figure 8. Left Lane-Offset Change for Lane Change and Departure Events From Safety Pilot

Identifying Active Braking versus Coasting

Although the data indicated whether the HV driver braked between the alert and 4 sec after the alert, the same information was not available for the LV. Since a braking lead vehicle triggers brake lights, but a coasting lead vehicle does not, we used an algorithm to separate these two deceleration scenarios. Details of this algorithm are provided in Appendix B.

The host vehicle deceleration distribution from the OnStar dataset is shown in Figure 9. The figure shows an inflection point at approximately -0.55 m/s^2, where it is inferred that the mechanism of deceleration changes from coasting (release of accelerator) to active braking. Thus, if the average acceleration of the LV was less than -0.55 m/s^2, then the LV was considered to be actively braking (rather than coasting).

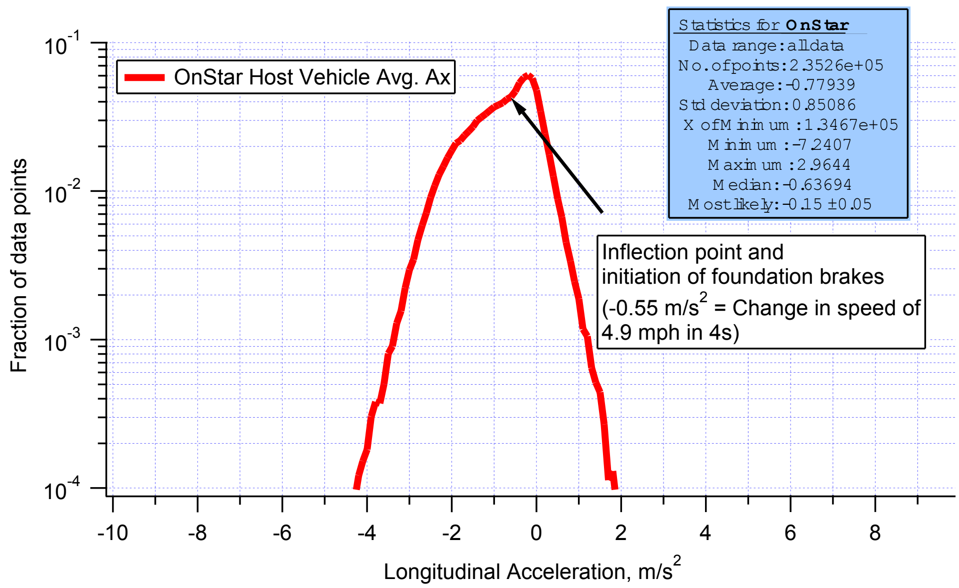


Figure 9. Distribution of average host vehicle acceleration between the FCA Imminent Alert and 4 seconds following the alert.

Identifying FCA Imminent Alert Scenarios

Building upon the lane change and lead-vehicle-braking algorithms described above, we developed seven FCA imminent alert scenarios that were exhaustive and mutually exclusive. These were chosen to correspond generally to FCA scenarios identified in the ACAS FOT, which employed a more detailed scenario classification that could be supported via the use of available video data.

Figure 10 presents a flowchart of the FCA alert categorization. At the top level, the key distinction is between FCA imminent alert events where the LV remains 4 seconds after the alert (i.e., an "in-path" vehicle scenario) versus events where this is not true. These latter cases include events where there is either no LV 4 seconds after the alert or a new lead vehicle appears 4 seconds after the alert. For analysis purposes, all cases in which the LV does not remain in path after 4 seconds are treated equivalently.

Alerts in which the lead vehicle remains "in path" (shown on the left side of Figure 10) are further divided into three categories based on the behavior of the lead vehicle: LV slowing, LV stopped, and LV moving at a constant speed or accelerating. These first two categories of alerts are of potentially greater interest, since they correspond to scenarios where driver braking action is more likely required to resolve the situation relative to the third category (LV moving at a constant speed or accelerating).

Alerts where the LV changes or no vehicle is detected 4 seconds after the imminent alert fall into three categories shown on the right half of Figure 10. First, out-of-path alerts are characterized by the estimated presence of an oncoming lead vehicle (as detected by the system). In this scenario, the oncoming vehicle is judged to be in a different (oncoming) lane and the system is assumed to have misidentified the threat as being in path and moving in the same direction as the HV. Similar events were identified in the Safety Pilot dataset using a Mobileye-based FCA system, where forward-looking video could be used to confirm that these alerts largely consisted of oncoming vehicles in an adjacent lane. Host-vehicle lane change alerts occur when the HV changes lanes and during this lane change approaches the vehicle in its original lane in a manner that triggers the FCA imminent alert. These are identified by the presence of a lane-change maneuver on the part of the HV after the alert. Finally, the remaining cases are categorized either as ones in which the LV turns or changes lanes out of the path of the HV, or as unknown. This latter category is probably the least homogeneous, since it includes any alert that could not otherwise be classified.

Figure 10 also shows the estimated proportion of each category among FCA alerts in this dataset. “In-path” alerts made up just over 50 percent of the sample, with LV at a constant speed or accelerating making up 31 percent of the sample, followed by LV slowing at 19 percent of the sample. The in-path LV stopped case made up less than 1 percent of all alerts. Out-of-path (OOP), on-coming traffic alerts made up 2 percent of the sample, while HV lane change, LV turn or lane change, and unknown motions together combined to make up 48 percent of the sample.

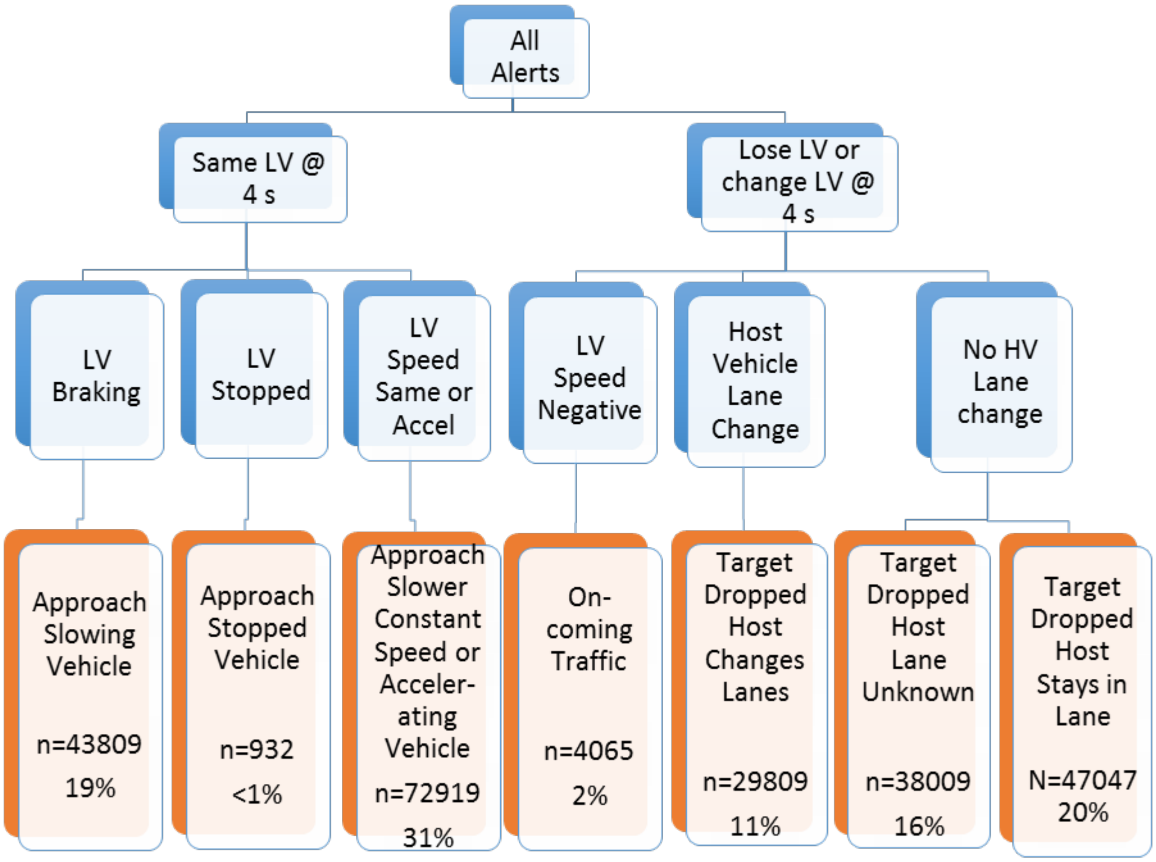


Figure 10. FCA Imminent Alert Scenario flowchart (HV=host vehicle, LV= lead vehicle)

Normal Driving Behavior

The normal driving statistics were created using the available trip-by-trip counter data collected by the OnStar system. To create the normal driving statistics the counter data from the OnStar system was aggregated over the course of the study (for studying setting choices) or for each month of the study (for studying adaptation in normal driving). These included:

- Proportion of time over left lane boundary,[1]
- Proportion of time over right lane boundary,[2]
- Proportion of time driving under 35 mph (which was the reference level used in the analysis), between 35 mph and 55 mph, or over 55 mph,
- Proportion of time following another vehicle,
- Average follow distance when following,[3]

[1] Calculated as proportion of the time when lane boundary confidence is high that the center of the vehicle is within 1 m (39 inches) of the left lane boundary.
[2] Calculated as proportion of the time when lane boundary confidence is high that the center of the vehicle is within 1 m (39 inches) of the right lane boundary.

- Average monthly miles, and
- Preferred Alert Type setting: safety alert seat versus beeps (applicable to Cadillac XTS and SRX).

The counters were processed in one of two ways. For the variables that had pre-specified ranges of interest, the driving statistics were calculated directly from this data, including over lane proportions and the proportion of driving in 35 to 55 mph or 55 mph+. The over lane proportions were drawn from histograms that tracked the time that the vehicle's camera (positioned at vehicle centerline) was within 1m of the appropriate lane boundary. Since the vehicles in this study were approximately 1.85 to 1.90 m wide, any time these counters were incremented the vehicle was assumed to be over, or nearly over, the lane boundary. The speed bin cutoffs were determined by both ranges of interest and the available counter data, since speed was tracked in histograms.

The next two normal driving statistics are average following distance and proportion of time following a vehicle ahead. These were both stored in a series of histograms broken down by driving speed. This meant that there were multiple ways to form the driving statistics. To begin, the average following distance and proportion of time following were calculated for all of the available speed ranges. These values were then analyzed with principle components analysis (PCA). The results of the PCA indicated that the vast majority of the variability was captured by the first principle component, which was essentially an average of all the counts. The second principle component indicated that there might be some information in the difference between the following distance at lower speeds and at upper speeds, but this only accounted for a small amount of variability. During the first round of model fitting, these statistics were split into two values each, one for speeds of 45 mph or less and the other higher than 45 mph. These values proved to be highly correlated and the two speed ranges were never significant in the same model. As such, they were simplified to a single value each, combining all the speed histograms. Finally, the normal driving statistics were standardized to increase interpretability of effect sizes across the factors examined.

System Availability

Availability (ready-to-assist or RTA) rates were constructed using histograms of speed and not-ready-to-assist (NRTA) counters. Since the systems are always unavailable under the design speed thresholds (25 mph for FCA and 35 mph for LDW), the analysis of the availability rate was conducted for the speed ranges greater than these thresholds. Beyond minimum operating speeds for the FCA and LDW systems evaluation, it should be noted that FCA alerts are only available only when a target is detected ahead by the FCA system in the same lane as the host vehicle (i.e., closest in-path vehicle or CIPV).

Figure 11 and Figure 12 show histograms of the average RTA rates per vehicle for LDW and FCA, respectively, broken down separately for each vehicle model. Their characteristics are very similar regardless of vehicle model. The median rates are about 80 percent for LDW and 90 percent for FCA; with the SRX showing a slightly higher availability rate compared to the other models for both the LDW and FCA systems. The long-tailed distributions to the left in both figures indicate that some vehicles had low system availability, and that availability rate is significantly vehicle-dependent (particularly for LDW).

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[3] Calculated using histogram data collected by OnStar. The centerpoint of each histogram bin was used to determine the distance value for the time spent in that bin.

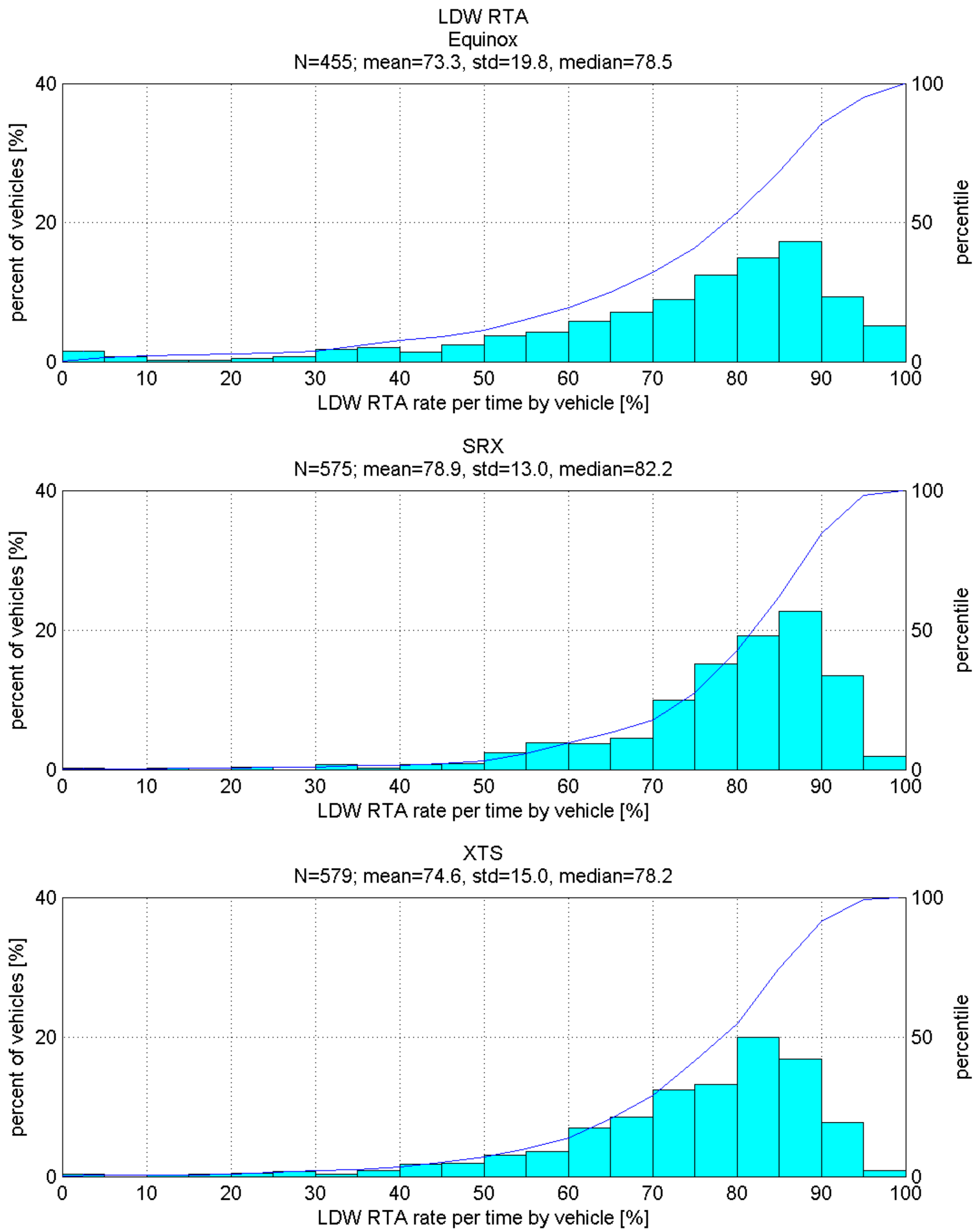

Figure 11. Distribution of availability rate of LDW by vehicle

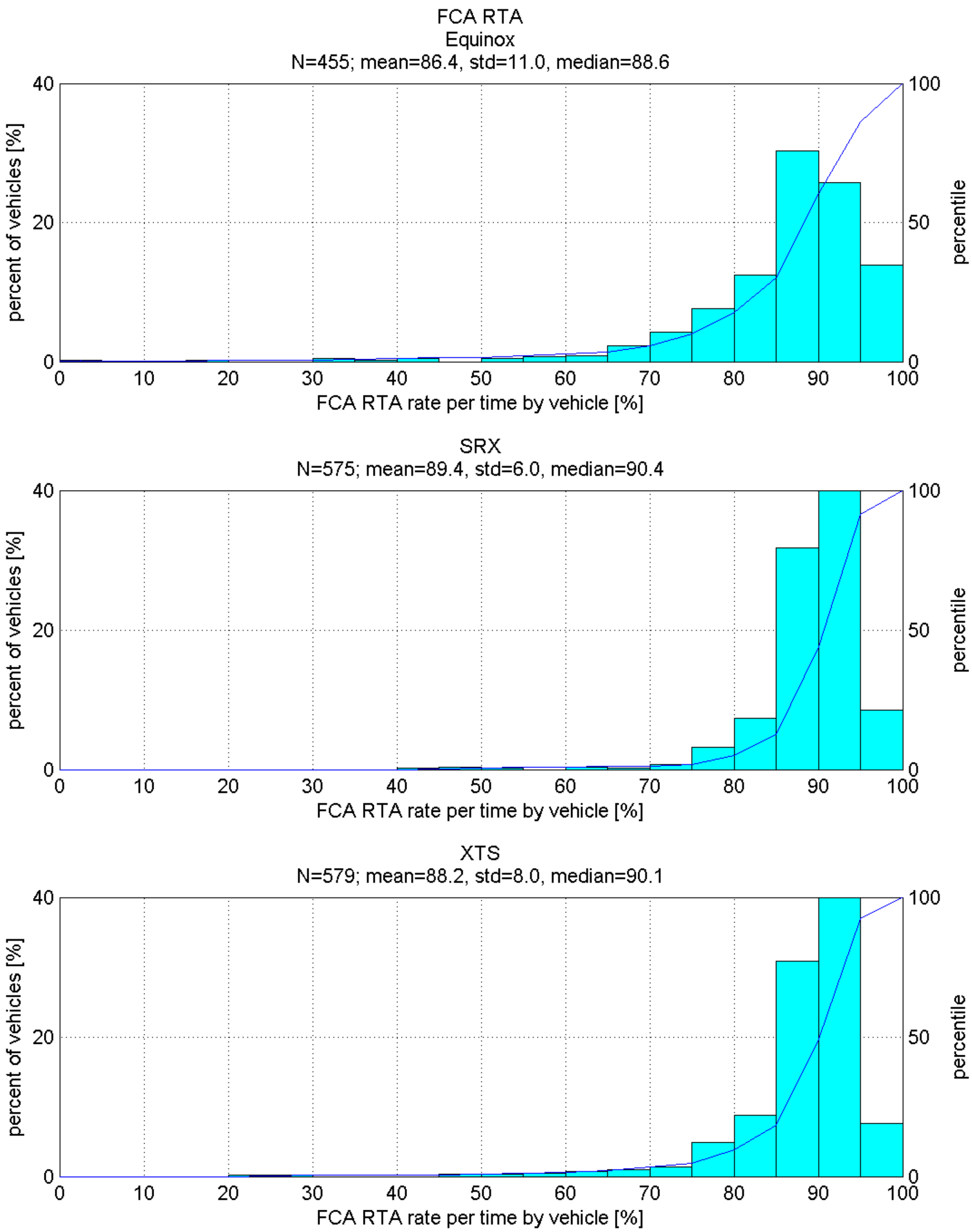

Figure 12. Distribution of availability rate of FCA by vehicle

Reasons for NRTA conditions were investigated by looking at LDW and FCA NRTA counters, shown in Table 13. However, because of data issues with NRTA (described in Appendix A), only adverse weather and low visibility were considered reliable for FCA. If NRTA occurs for multiple reasons at the same time, both reasons are independently recorded in the respective counters, and therefore the sum of those counters for all the unavailability reasons can be greater than the total driving time. Table 14 shows the breakdown of the LDW and available FCA NRTA reasons as a percent of driving time over threshold. Although the minimum-speed threshold for LDW is 35 mph, the speed counter bin extended from 25 to 45 mph. Thus, rather than try to split the bin, we used only bins with speed known to be above the system operation threshold (i.e., speeds above 45 mph).

Table 13 Reasons for the system unavailability

Bit	LDW	FCA
0	Speed under threshold (35 mph)	Speed under threshold (25 mph)
1	Adverse weather	Adverse weather
2	Low visibility	Low visibility
3	Invalid left lane position	Speed above threshold (255 mph)
4	Invalid right lane position	
5	Single-lane performance	
		Closest-in-path vehicle not detected

Table 14 Reason for NRTA as a percent of driving time over 45 mph

Not-Ready-to-Assist (NRTA) Reason	LDW NRTA as Percentage of Driving Time at >45 mph	FCA NRTA as Percentage of Driving Time at >25 mph
Speed below threshold	0.22%	N/A
Adverse weather	0.07%	0.08%
Low visibility	0.02%	0.02%
Left lane not valid	11.8%	N/A
Right lane not valid	12.6%	N/A

Driver Behavior

Acceptance (Choice of LDW and FCA System Settings)

Driver acceptance in this study was measured by the choice of settings over the course of the study. This information was summarized in trip histograms that indicated the total time of each trip under each setting.

The total driving time in each alert type setting for the three vehicle models is shown in Figure 13. The selected setting applied to both FCA and LDW. As the graph indicates, Equinox drivers had only the beeps setting, but Cadillac drivers could choose for alert type either beeps or the safety alert seat (SAS). Cadillac drivers used SAS for approximately 90 percent of the total driving in this study.

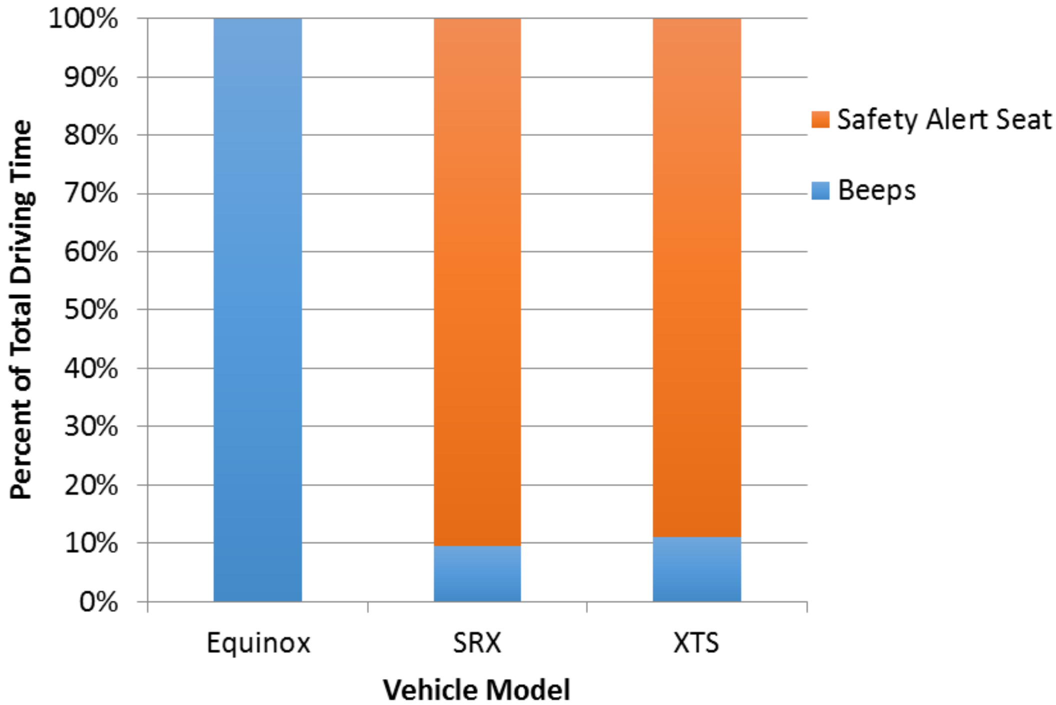

Figure 13. Percentage of total driving time for each alert type

LDW

Table 15 shows the percent of time for which LDW was on or off, both overall, and as a function of Alert Type settings (safety alert seat versus beeps). Overall, LDW was on about 50 percent of the time. However, when the safety alert seat Alert Type setting was selected on the XTS and SRX, system usage doubled (from 32% to 64%) relative to Equinox drivers that are not provided the SAS option (and instead are only provided beeps). The subset of SAS users who also had a Heads-Up Display (HUD) was associated with an intermediate use rate at 56 percent.

Table 15 Percent LDW Setting by Interface

Setting	Overall	Beeps	Safety Alert Seat (Haptic Seat)	Safety Alert Seat (Haptic Seat) +HUD
On	49.6	31.9	63.8	56.8
Off	50.4	68.1	36.3	43.2

We used a multivariate logistic regression model to predict LDW setting as a function of driving time and trip characteristics. The unit of analysis was a trip, and each trip was classified by the majority (i.e., highest percentage) setting on the trip, based on the system setting counters. Other predictors were restricted to those measures that are available at the trip level, including primary driver age and gender, trip distance (miles), sun elevation measured at end of trip (degrees), and the fraction of trip at high speeds (55mph+). Sun elevation is a measure of outdoor light level, and the end-of-trip measure is used here because some trips have no alerts and therefore no sun elevation samples during the trip.

Each vehicle's odometer reading at the end of the trip was treated as the time variable, which takes into account that different drivers accumulate alert experiences at different rates.

The full model, built using the general estimating equations (GEE) method, is provided in Appendix C. Non-significant predictors were excluded from the model and significant interaction terms were included. Significant predictors include odometer, fraction of the trip at 55+mph, number of LDW alerts on the trip, age, gender, vehicle model, trip length, HUD available, and night. Interactions include vehicle type X odometer, vehicle type X night, and vehicle type X gender. For odometer, there is a flattening (or stabilization) of setting proportions at 10,850 miles, which was modeled using a piecewise model.

For odometer readings less than the 10,850-mile cutoff, there is significant effect of odometer (modeled on a log scale) with increasing odds of the system being turned off. The Cadillac models have both significantly lower starting odds of having the system Off and a slower rate of increase in having the system turned off as compared to the Equinox. Over these for 10,850 miles, Equinox drivers increased their Off rate from 38 percent to 78 percent on average. SRX drivers increased their Off rate from an average of 20 percent to 38 percent, and XTS drivers increased their Off rate from an average of 32 percent to 40 percent over the first 10,850 miles. Figure 14 shows observed and modeled proportions of trips with LDW Off (the majority of the time) as a function of odometer and vehicle type.

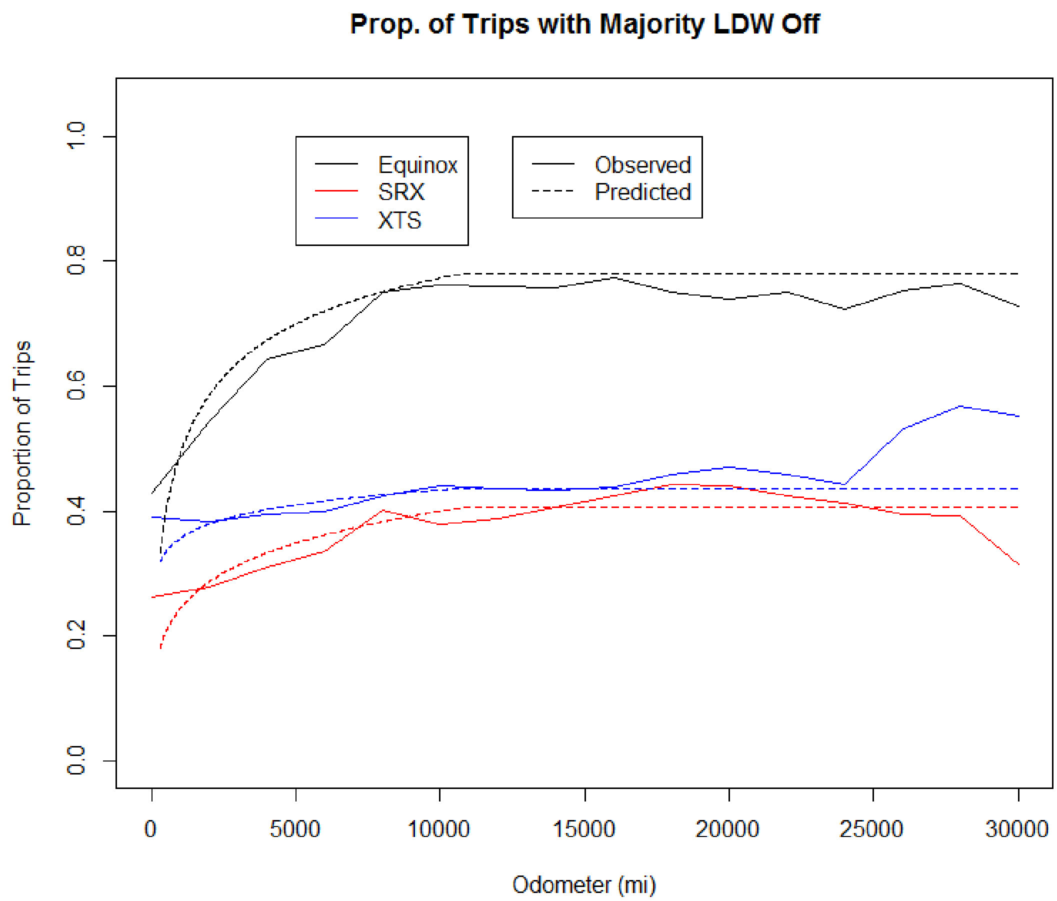

Figure 14. Proportion of trips with LDW Off (for the majority of the trip) by odometer for each make/model. Observed proportions are shown with solid lines and corresponding modeled values are shown with dotted lines.

Increased age predicts a lower odds of system deactivation (about 1% decrease per year of age) as does proportion of the trip at high speeds (for every 1% increase in trip proportion over 55 mph, the model predicts a 0.5 percent decrease in the odds of system deactivation). Presence of the HUD has the opposite effect (14% increase in odds of system deactivation) as do higher numbers of LDW alerts on the trip (presented to the driver or not). For every additional alert on a trip, the odds of system deactivation increase by 4 percent.

Gender and the ending lighting conditions have substantially different effects between vehicle models. Men driving an Equinox have 11 percent lower odds of turning the system off compared to women, but this trend is reversed for the SRX (18% higher odds of Off for men) and XTS drivers (12% higher odds of Off for men). Trips that end after civil dusk are more likely to have the system predominantly off for Equinox drivers, increasing the odds by about 18 percent, but the reverse is true for SRX drivers, for whom the odds of turning the system off fall by about 7 percent under similar circumstances. Drivers in XTS model vehicles see a small but non-significant increase in their odds of disabling the LDW system for trips ending after dusk.

It should be noted that odds ratios are not the same as risk ratios, particular in this context. In most cases, odds ratios will be higher than their corresponding risk ratios. However, risk ratios can only be computed for specific values of other model predictors (e.g., a 45-year-old XTS driver with 50% of trip above 55 mph, 4 LDW alerts, haptic setting, no HUD, and a trip ending during the day). Thus, interpretation of the odds ratios is best done in relative terms. For example, in this analysis, odometer over the first year has the largest effect on system setting rates of all of the predictors, and the effect of a 10-year increase in age is about the same magnitude as the gender effect for Equinox.

A second logistic regression model was built to investigate the relationship between normal driving behavior and LDW setting choice. The dependent variable was the dominant setting choice for a trip. Predictors were aggregated over all driving for a given vehicle and included proportion of time over left lane boundary and over right lane boundary, proportion of time driving under 35 mph, between 35 mph and 55 mph, and over 55mph, proportion of time following another vehicle, average follow distance when following a detected vehicle, average monthly miles, safety alert seat use (yes/no), driver age and gender, vehicle model and HUD use. Normal driving statistics were standardized across vehicles so that effect sizes could be more readily compared across those predictors. The full model is provided in Appendix C. Significant predictors were the proportion of time over the right lane, proportion of speed in the 35-55 mph range, average following distance, average monthly miles, SAS availability (Cadillacs only), HUD availability, SAS use, and the interactions of SAS with each of over right lane proportion and average monthly mileage.

For the LDW setting model, the normal driving statistics are generally influential. Individuals who are one standard deviation above the average for proportion of time driven over the right lane boundary have odds of disabling the system 43 percent higher than drivers at the average proportion. The effect of driving in the 35-55mph speed range is similar, with a one standard deviation increase in the proportion of time driving in that range scaling the odds of disabling the system by 48 percent. Both of the effects described above are only seen for Equinox drivers, however. Increasing the average monthly miles has a similar effect, also leading to increased odds of system deactivation (odds ratio of 1.42). In the other direction, individuals with an average following distance one standard deviation above the mean for the sample tend to leave the system enabled (odds ratio reduction of 9%). As can also be seen in Table 15, having the SAS available (i.e., vehicle is SRX or XTS) also markedly decreases the probability of turning off the LDW system, and the effect almost doubles when SAS is the dominant alert type for the driver (both SAS availability and use have an odds ratio of approximately 0.5). Conversely, the presence of a HUD, only possible in a subset of the vehicles with SAS, increases the probability of deactivating the system. When both SAS and a HUD are available, the odds of deactivation are 37 percent less than for a beeps-only vehicle; when SAS is available without a HUD, odds of deactivation are 50 percent less than for a beeps-only vehicle. Finally, if the SAS is used for the majority of the study, the trend toward system deactivation seen for individuals with above average monthly mileage is markedly reduced as well.

FCA

Table 16 shows the percent of time for which FCA was in each alert timing setting, both overall and for specific FCA imminent alert types. Overall, FCA was on about 91 percent of the time. However, with the safety alert seat selected, the system was turned on 97.5 percent of the time, compared to 84.3 percent for drivers who used beeps (Equinox drivers and 10 percent of Cadillac drivers). The subset of

SAS users who also had a head-up display (HUD) was associated with use rates of 94.5 percent. Far was the most popular setting, followed by Medium, Near, and Off.

Table 16 Percent FCA Setting by Interface

Setting	Overall	Beeps	Safety Alert Seat (Haptic Seat)	Safety Alert Seat (Haptic Seat) +HUD
Near	15.1	13.7	13.9	6.7
Medium	17.2	22.1	17.9	15.3
Far	58.7	48.6	65.7	72.5
Off	9.0	15.7	2.5	5.5

Multivariate generalized logit models were used to model the multinomial probabilities of the four FCA settings as a function of trip characteristics. The unit of analysis was a trip and trip-level setting was defined as the dominant (highest percentage) setting for the trip. Potential predictors considered included: driver age and gender, trip distance (miles), trip ending after dusk (yes/no), and fraction of trip at high speeds (55mph+). Each vehicle's odometer was treated as the time variable, allowing for different drivers to accumulate experience at different rates.

The full model, built using the GEE method, is provided in Appendix C. Non-significant predictors were excluded from the model and interactions were considered. Because multinomial models involve more than two levels of the dependent variable, we selected Far as the reference setting for comparison purposes. Thus, the model presented consists of three sub-models that describe the odds of setting the FCA to one of the other three settings as opposed to the odds of setting the FCA to the Far setting. It is possible to re-parameterize to compare any two settings, but we present results in this way to try to simplify an already complex model.

Odometer, driver age and vehicle model were significant in all three sub-models. In all cases, increasing odometer results in vehicles initially moving away from the Far setting, but interestingly, the significant quadratic term in the Far versus Off and Far versus Medium sub-models leads to an increase in the odds of Far after about 12,000 miles. This pattern holds for all three vehicle models and is shown in Figure 15 (Equinox), Figure 16 (SRX), and Figure 17 (XTS). Consistent with the results shown in Table 16, drivers of both Cadillac models (equipped with the safety alert seat) show a higher preference for the Far setting in general than the Equinox (SRX: 66% lower odds of Off, 73% lower odds of Near, and 57% lower odds of Medium than Equinox; XTS: 40% lower odds of Off, 60% lower odds of Near, and 52% lower odds of Medium than Equinox). In addition, the time trends for the Cadillacs are much less pronounced than for the Equinox.

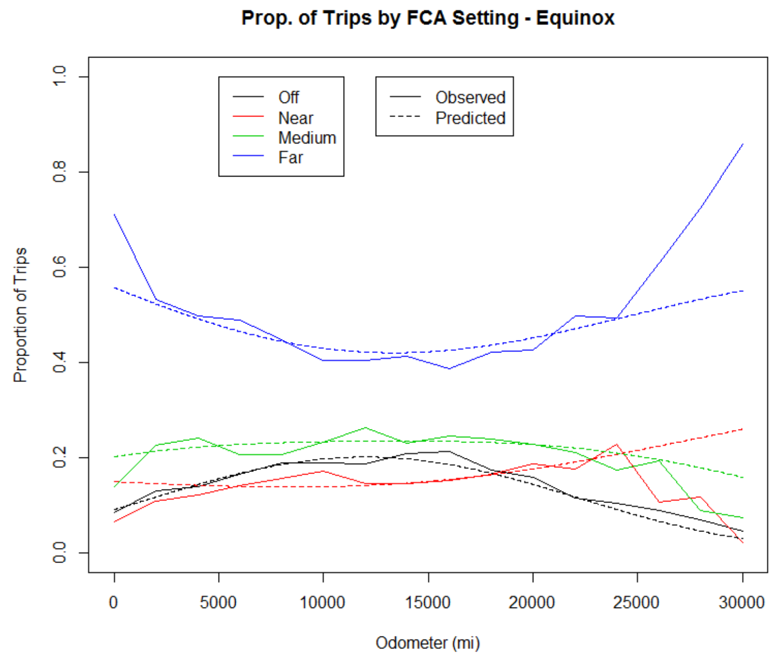

Figure 15. Observed (solid) and modeled (dotted) proportion of each FCA setting as a function of odometer for the Equinox.

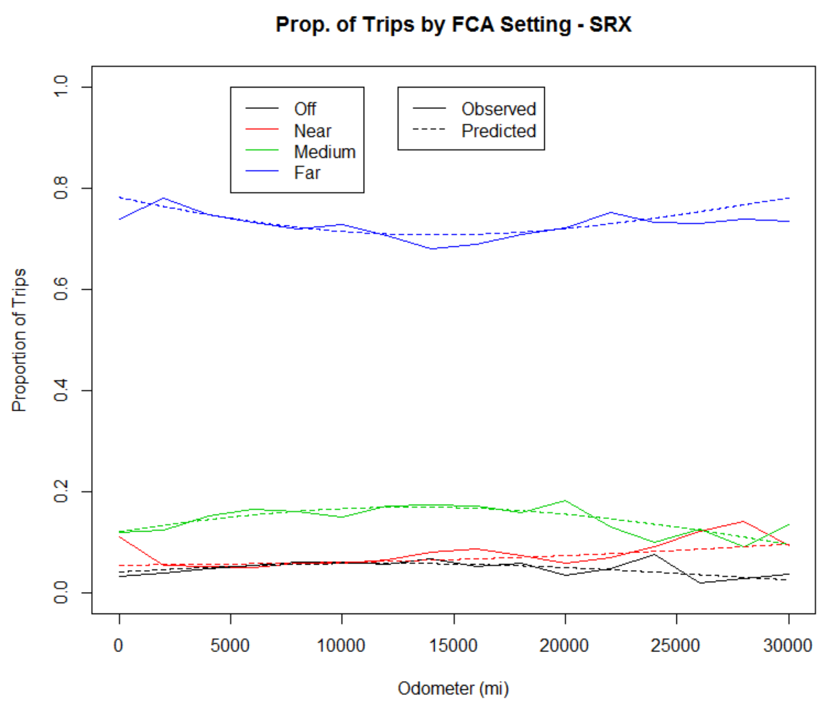

Figure 16. Observed (solid) and modeled (dotted) proportion of each FCA setting as a function of odometer for the SRX.

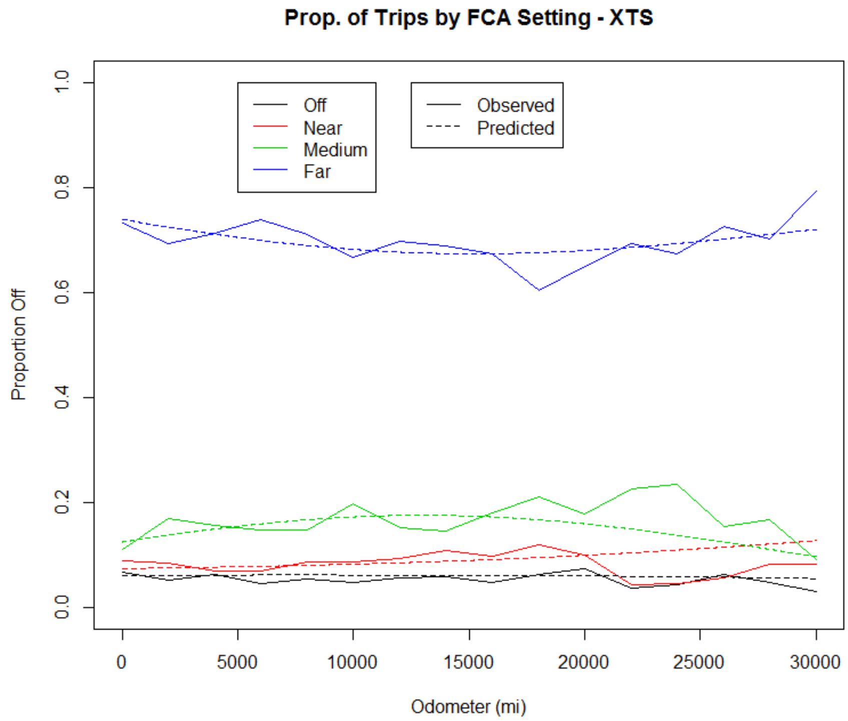

Figure 17. Observed (solid) and modeled (dotted) proportion of each FCA setting as a function of odometer for the XTS.

Increased age tends to increase the odds of the FCA being left on the Far setting, but the effect weakens as the comparison setting becomes more similar. For example, a 10-year increase in age is associated with 20 percent lower odds of Off (compared to Far), 7 percent lower odds of Near, and 4 percent lower odds of Medium.

The fraction of the trip spent at speeds of 55mph or greater is significant in differentiating between Far and Off or Far and Medium, in both cases favoring the Far setting. Trips with an additional 10 percent of time spent above 55 mph have 3 percent lower odds of using Off and 2 percent lower odds of using Medium. Near versus Far is not predicted by the fraction of trip over 55 mph.

Finally, the presence of a HUD and trips ending after dusk only have a significant effect on the odds of Off versus Far. Drivers with the HUD available were much less likely to select Off compared to Far, though the size of the effect decreases with increasing age (e.g., at age 40, drivers of HUD-equipped vehicles have 90 percent lower odds of Off [versus Far]; at age 50, those drivers have 80 percent lower odds of using the Off setting [versus Far]). The effect of night was to increase the odds of Off by 7 percent for Equinox drivers and decrease the odds of Off by 21 percent for Cadillac drivers.

A second multivariate generalized logit model was developed to look at the relationship between normal driving behavior and FCA setting. The resulting FCA model again consists of three sub-models (see Appendix C). Significant predictors include age, vehicle model, proportion of time spent following and the vehicle model X proportion of time following interaction.

Increasing age has a small but significant effect, resulting in a 16 percent decrease in the odds of Off and an 11 percent decrease in the Odds of Near for every additional decade of age. For the Medium setting, the age effect is not significant, but there is a sizable effect of average follow distance, such that Equinox drivers who follow more closely have a higher likelihood of choosing the Medium setting (1 sd closer average following results in 30 percent greater odds of choosing Medium over Far).

In all three sub-models, the existence of the SAS as an option (i.e., Cadillac models) is highly significant, and markedly decreases the odds of settings other than Far. SRX drivers have 74 percent lower odds of Off, 74 percent lower odds of Near, and 60 percent lower odds of Medium compared to Equinox drivers. XTS drivers have 74 percent lower odds of Off, 56 percent lower odds of Near, and 60 percent lower odds of Medium compared to Equinox drivers.

Alert Rates

For both FCA and LDW, alert rate was examined using alerts per 100 miles (rather than the miles between alerts measure also provided earlier in the Descriptive Statistics section). Modeling of alert rate was performed at the trip level, and focused on FCA imminent collision alerts and overall (combined left and right) LDW rates. Each rate was modeled using a Poisson rate model taking the trip distance in hundreds of miles as the exposure. Poisson regression is commonly used to model count data and it is able to take into account exposure. In this case, exposure is miles driven (in 100-mile increments) and the dependent variable is counts of alerts. Initial predictors included Day/Night status at the end of the trip, fraction of trip at high speeds (55mph+), odometer (miles; log-transformed), age (years), gender, vehicle model, and HUD presence. Details of both models, along with separate models of left LDW and right LDW rates are shown in Appendix C.

LDW

The significant LDW model parameters are log-odometer, vehicle model, proportion of trip over 55 mph, night, setting, HUD, and the log-odometer X setting, vehicle model X setting, and log-odometer X vehicle model interactions. The effect of odometer for different settings and vehicle models is shown in Figure 18. As previously shown in Table 10, overall alert rates are consistently higher when LDW is turned off. The results show that as the odometer increases, the LDW alert rate also increases (as a log function). The rate of increase is 3 percent slower for individuals with the system turned off, but having the system off increases the baseline number of alerts by over 200 percent on average. Among vehicle models, SRX drivers have a slightly lower (but not significantly lower) alert rate compared to Equinox drivers, while XTS drivers have a 37 percent higher starting alert rate. However, the change over odometer is 4 percent greater for SRX than Equinox and 3 percent less for XTS than Equinox. Thus, the starting alert rate and subsequent rate of change trade off somewhat for the Cadillacs. For Cadillac drivers, the alert rate in the Off setting is lower than for the Equinox (24% lower for SRX and 29% lower for XTS). Finally, presence of a HUD decreases alert rates by 5 percent, nighttime increases alert rates by 2 percent, and each additional 10 percent in the proportion of a trip at speeds over 55 mph results in an estimated 1.5 percent decrease in alert rate.

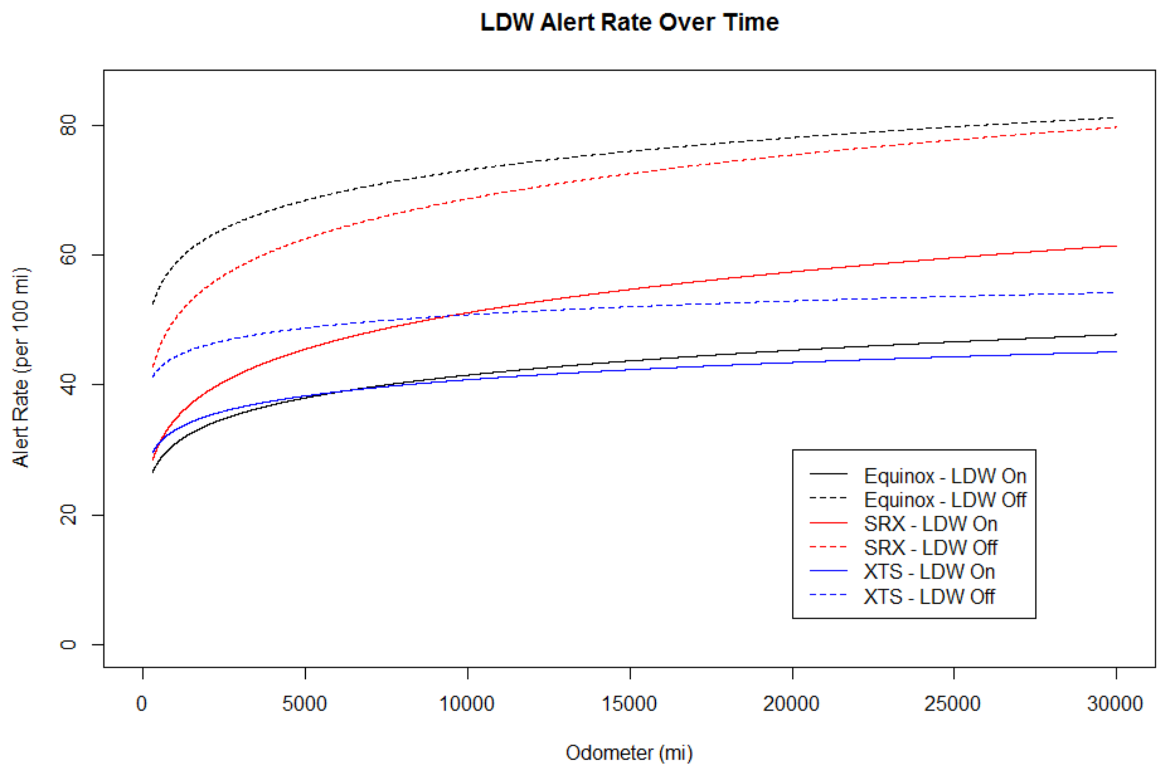

Figure 18. Predicted LDW alert rates per 100 miles as a function of odometer, vehicle model, and setting.

We conducted a second model of alert rate over time, focused on LDW alerts that are followed by a lane change versus those that are not. Lane changes were determined using the same algorithm that was used for the FCA scenario definition (see Appendix B). All lane changes were assumed to be unsignaled, since by design the LDW alert is suppressed if the signal is used in the direction of the lane change.

The models of alert rate for each LDW response category were Poisson rate models at the vehicle level. Log odometer and lane change (yes versus no) were the predictors and the results showed that there was not a decrease in the alert rate for suspected lane changes. The pattern is shown in Figure 19. Unsignaled lane changes made up about 20 percent of alerts at low odometer readings. Like the rate of non-lane-change LDWs, the rate of unsignaled lane-change alerts increases over time. Even though the absolute slope of the increase for lane-change LDW alerts is lower than that of non-lane-change LDW alerts, it is larger relative to the starting alert rate. As a result, the proportion of all LDWs, whether the system was on or off, that are categorized as unsignaled lane changes actually *increases* over odometer.

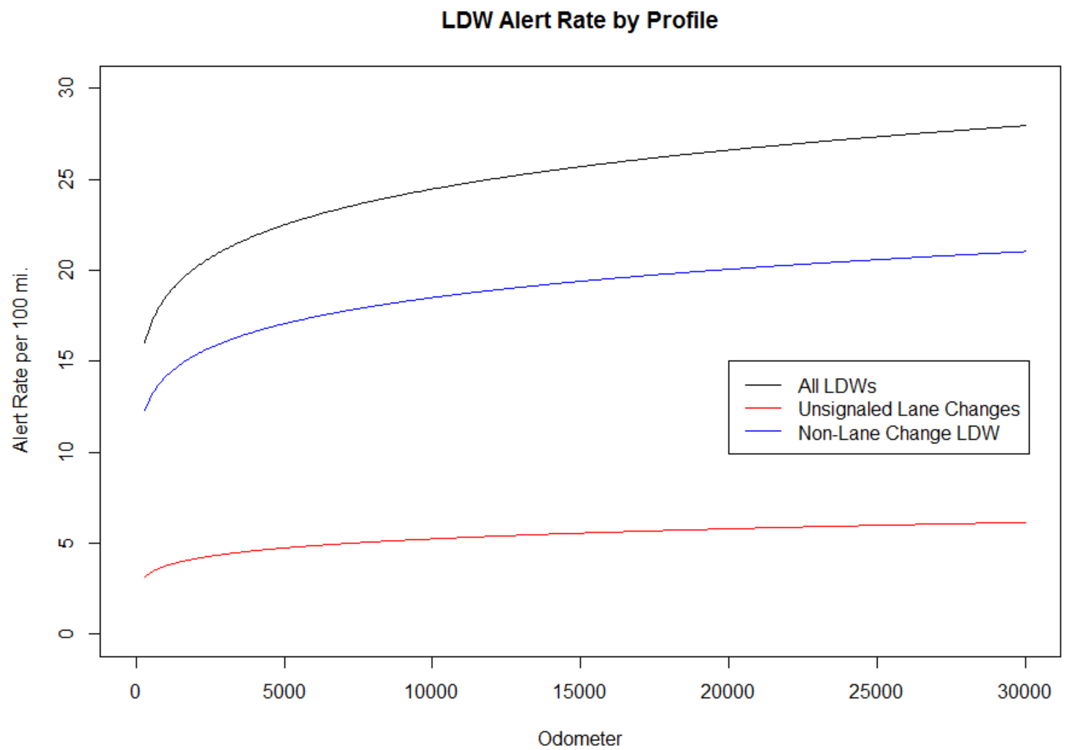

Figure 19. LDW alert rate as a function of odometer. Three models are shown: (1) All LDWs, (2) Unsignaled lane changes, and (3) Non-lane-change events.

FCA

The Poisson rate model of FCA imminent alerts per 100 miles was developed in the same way as for LDW alerts. The significant predictors include log-odometer, vehicle model, age, night, setting, HUD, gender, and the log-odometer X setting and vehicle model X setting interactions. In contrast to LDW alerts, regardless of setting, the FCA alert rate decreases as the odometer increases (on the log-scale). Though the rate decreases when the system is turned off as well, the rate of the decrease is smaller (about 65% of what it when the system is on). Drivers of Cadillac models have higher alert rates overall than the Equinox drivers (61% higher for XTS; 38% higher for SRX), but this difference is reduced for those individuals with the FCA turned off (Off alert rate 23% higher for XTS; 3.5% higher for SRX). Inclusion of a HUD decreases the alert rate by 11 percent, male drivers have a 28 percent higher alert rate compared to females, and each additional decade of age decreases alert rate by 24 percent. The alert rate decreases by 31 percent at night, though this may reflect traffic conditions rather than system or behavioral changes that occur during the day. Finally, the Near setting results in a 52 percent reduction in alert rate and the Medium setting results in a 25 percent reduction in alert rate, but this is inherent in the alert timing algorithms associated with these settings. The patterns of alert rate change over odometer as a function of vehicle model and setting are shown in Figure 20 (Equinox), Figure 21 (SRX), and Figure 22 (XTS). For the Cadillacs, Far and Off alert rates are similar, though they cross at around 10,000 miles where Off rates become higher. For the Equinox alert rates in the Off setting are generally higher than for Far across the entire odometer range.

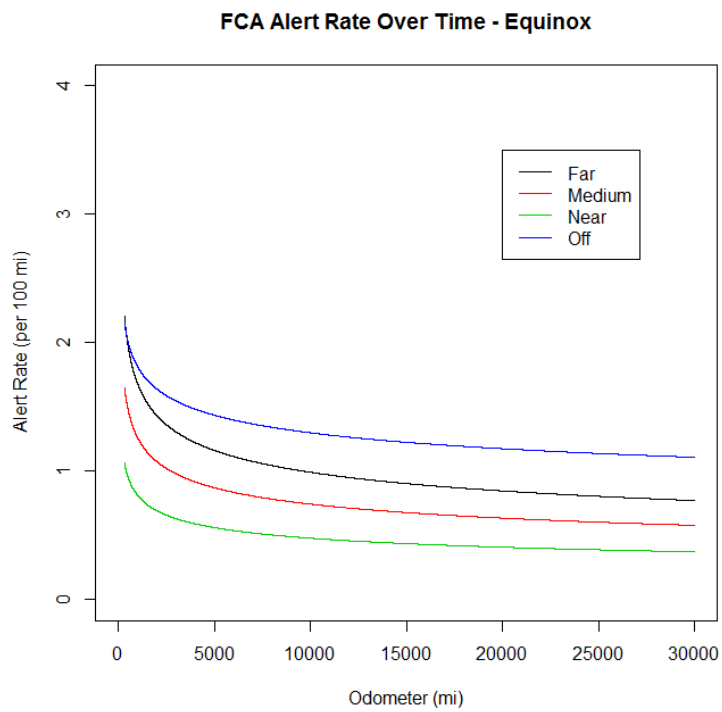

Figure 20. Modeled FCA alert rate as a function of odometer and setting for the Equinox.

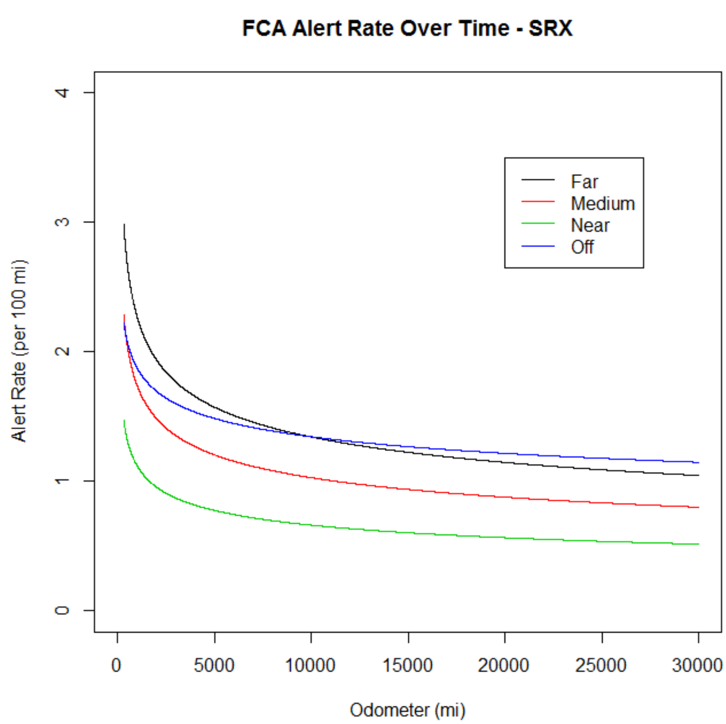

Figure 21. Modeled FCA alert rate as a function of odometer and setting for the SRX.

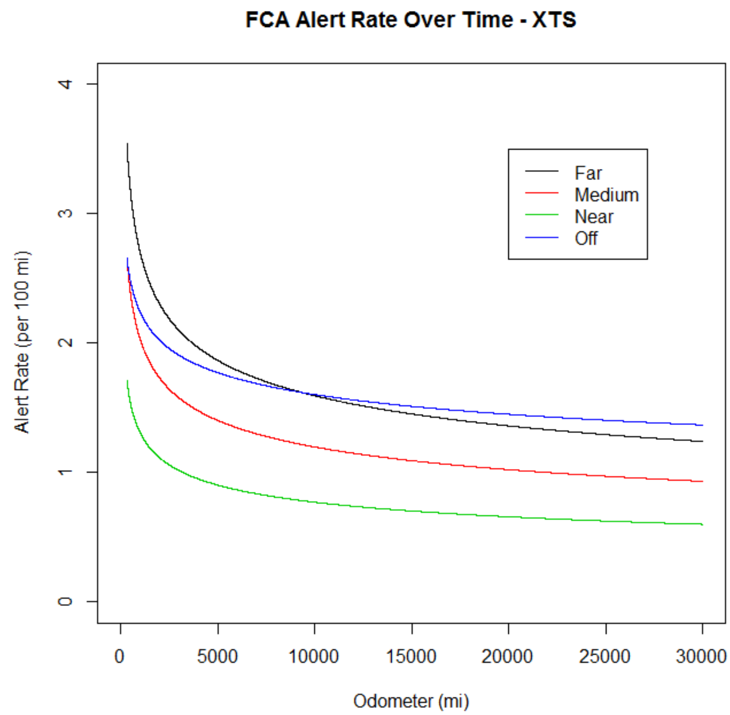

Figure 22. Modeled FCA alert rate as a function of odometer and setting for the XTS.

We were also interested in how alert rates change within each of the seven FCA scenarios, but because of small counts in some categories, we modeled these changes separately and at the individual vehicle level. For each vehicle, alert rate within scenario was aggregated on a monthly basis, along with median odometer for the month. For each vehicle, the intercept and slope of alert rate over log odometer was calculated. The trimmed means (computed for the middle 80% of values) and medians of the individual slopes for each scenario are shown in Table 17.

Table 17 Trimmed means and medians of the log-odometer coefficient for individual models of alert-rate change by scenario

Alert Scenario	**Mean logOdo Coef. Value**	**Median logOdo Coef. Value**
Overall Slope (All Scenarios)	-0.196	-0.182
Approaching Slowing Vehicle	-0.056	-0.094
Approaching Accelerating Vehicle	-0.204	-0.212
Approaching Stopped Vehicle	-0.145	-0.155
No Lateral Response, Lose Target	-0.177	-0.173
Lane Change Resolution	-0.081	-0.122
Oncoming Vehicle	-0.010	-0.052
Other	-0.184	-0.197

The pattern of changes in alert rates by scenario is illustrated in Figure 23. Because of the very different alert rates for the different scenarios, (e.g., note the extremely low alert rates associated with the approaching stopped vehicle and oncoming traffic scenarios), the vertical scales are not the same. Instead, each graph's vertical axis extends from a rate of 0 to the median initial rate for that scenario (at 0 odometer). Visually, the graphs show the decrease in proportion relative to the initial rate within a specific estimated FCA scenario. Thus, the OOP scenario (target lost—oncoming vehicle) shows almost no decrease over odometer, whereas approaching and accelerating in-path vehicle, approaching a stopped in-path vehicle, target lost—no lateral response and target lost—unknown lateral response decrease most (relative to the starting point).

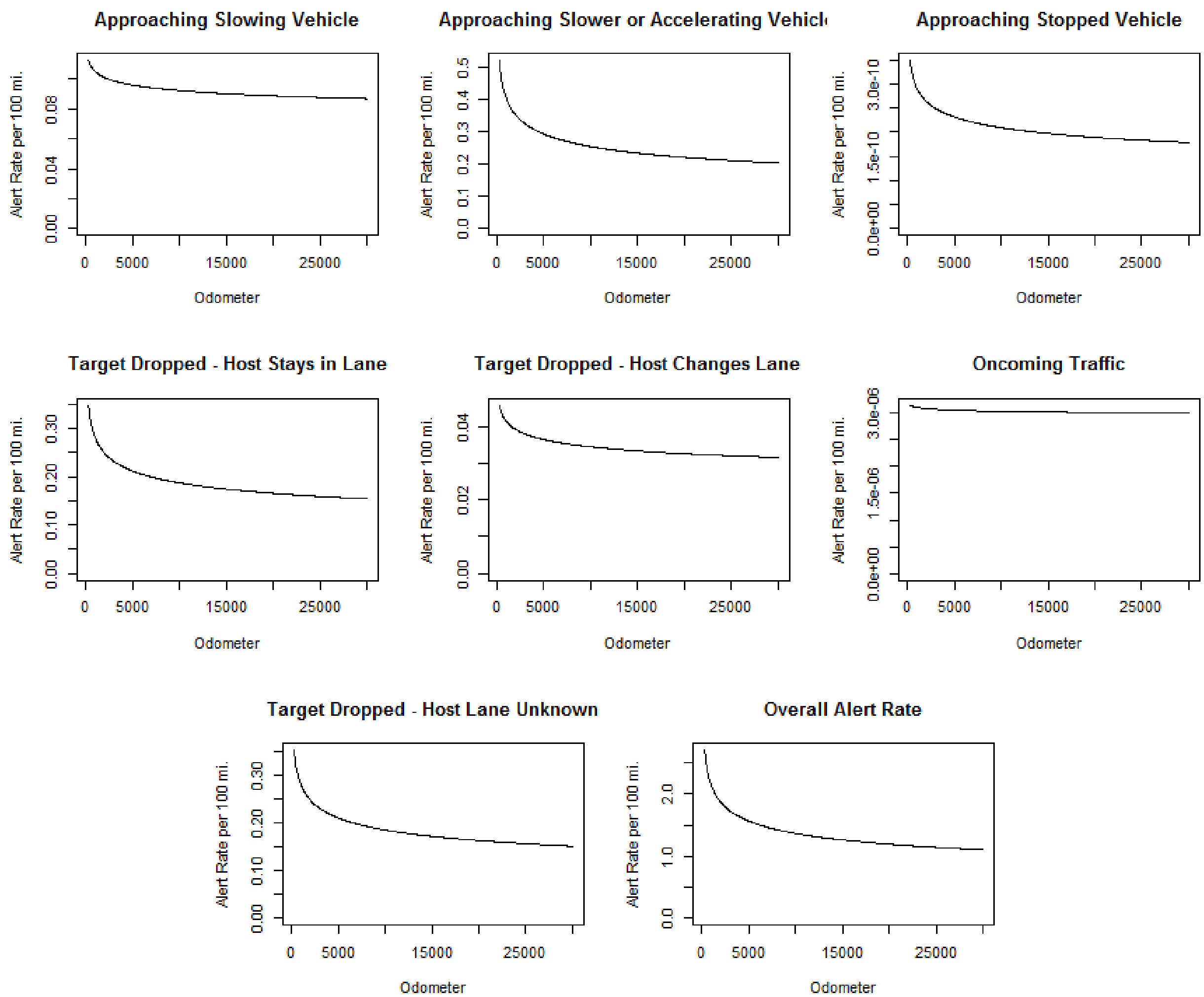

Figure 23. Graphs of median alert rate change over time by scenario. Note that the vertical axis scales are different across scenarios, but all range from 0 to the median initial rate.

Driver Response After FCA Alert

For FCA, we define three post-alert response measures. First, PABT is the time of initial braking that occurs after the FCA imminent alert within 4 sec. For analysis, we include only PABT values between

0.4 sec and 3 sec after the alert. We put these constraints on response time to exclude implausibly fast responses (i.e., responses that are likely to have been initiated before the alert) and slow responses (i.e., responses that are likely to have indicated a situation that did not require urgent response). In addition, we include only alerts in which the accelerator pedal was On and the brake pedal was Off at alert. While a driver in this condition may or may not be aware of the situation, these cases are indicative of a driver who is not already physically initiating his/her response.

A second measure of post-alert response is the deceleration between the time of the alert and 4 seconds after the alert. Average post-alert deceleration is the difference between speed at 4 sec following alert and speed at the time of alert onset, divided by 4. This represents the average deceleration achieved in the 4-sec post-alert timeframe, however it was achieved. This value is negative when the driver decelerates, and is measured in m/s^2. (Note deceleration in g's can be approximated by dividing by 10.)

The third response measure was a binary measure of response/non-response. Non-response was defined as the failure to initiate braking within 3 sec after the alert occurs. We assume that if braking did not occur within 3 seconds, it was not required to resolve the situation.

The distribution of PABT for drivers on the accelerator pedal and off the brake at alert is shown in Figure 24. Due to the sharp cutoff on the left, we used log(PABT) as the dependent measure for statistical modeling purposes.

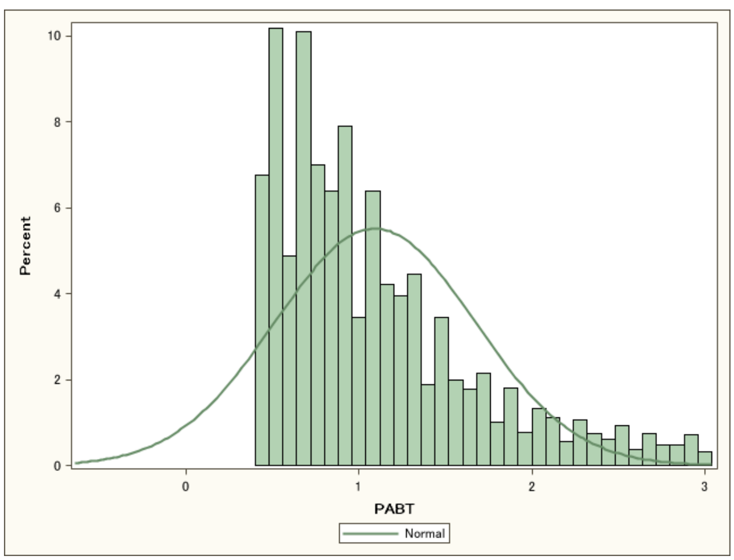

Figure 24. Distribution of post-alert braking time .

A linear mixed model was developed to predict log-transformed PABT as a function of available alert-level predictors. These included setting, road type, speed at event, wiper state, following distance at event, night/day, vehicle model, HUD, SAS, scenario, age, gender, and odometer. Age, gender, and odometer were not significant in this model. Interactions were also explored and three were significant: setting X SAS, following distance X road type, and following distance X scenario. Significant predictors and F tests are shown in Appendix C.

Table 18 presents the mean PABT for levels of key variables. Note that because the original models predicted the logarithm of PABT, the means shown are the exponential of the least squares means of log PABT. Drivers who turned the system off were 0.09-1.12 sec slower than the response time for drivers who used other settings, on average. Notably, PABTs with the Off setting were just over 0.10 sec slower than drivers who used the "matched" (same alert timing algorithm) Far setting. Across response scenarios, LV slowing and LV stopped elicit the fastest mean response, whereas LV accelerating/constant speed and all loss of LV scenarios result in mean response times of more than 1 second. The effect of road type is that responses to alerts on major roads are faster than responses on minor roads. The difference between mean response time on interstates and major collectors is 0.1 seconds. Mean response time is 0.15 sec slower when wipers are on compared to off, and night responses are 0.07 sec slower than daytime response on average. Finally, greater speed at time of alert was associated with slower PABT (approximately 0.13s longer mean response time per 10 mph increased speed).

In addition, PABTs of Equinox drivers were fastest on average, followed by SRX and XTS, with a difference between Equinox and XTS of 0.07 seconds. Also, responses were 0.05 seconds slower when the HUD was used and were 0.03 seconds slower when SAS was selected. However, as noted earlier, relatively small differences in the FCA and LDW alert timing experienced by the driver may exist across vehicles due to differences in vehicle-related factors, and hence these differences should be treated with caution. This caveat has particular relevance to these PABT results involving Vehicle Model, HUD, and Alert Type (with the largest difference in means being 71 ms).

Table 18   Least squares means for main effects in PABT model

Effect	Level	Mean PABT (s)
Response Scenario	New or No LV and Host Lane Change	1.211
	New or No LV and No Host Lateral Response	1.042
	New or No LV and Unknown Host Lateral Response	1.140
	New or No LV and LV Oncoming	1.134
	Same LV and LV Slowing	0.822
	Same LV and LV Stopped	0.844
	Same LV and LV Accelerating	1.139
Road Type	Interstate	0.991
	Principal Arterial-Freeways and Expressways	0.986
	Principal Arterial-Other	1.027
	Minor Arterial	1.092
	Major Collector	1.094
Vehicle Model *	SRX	1.031
	XTS	1.076
	Equinox	1.005
Wiper	Wiper On	1.115
	Wiper Off	0.964
Time of Day	Night	1.070
	Day	1.005
HUD *	Head-Up Display On	1.060
	Head-Up Display Off	1.014
Alert Type *	SAS	1.050
	Beeps	1.024
Setting	,	0.999
	Near	1.027
	Off	1.116
	Far	1.010

Note: * Effect may be due to vehicle differences with respect to alert timing experienced by driver.

In general, longer following distances were associated with slower response time (on average, each 10m additional following distance predicts a 0.05s increase in response time). However, the specific effect is affected by interaction terms. For example, the following distance X road type interaction indicated that the effect was smallest for major collectors (0.05s slower response per 10m additional following distance) and largest for principal arterials--freeway and other (0.08s slower response per 10m additional following distance). The following distance X scenario interaction indicated that the following-distance effect was only present in scenarios where the LV was not detected to be present 4 seconds after the alert and the HV did not change lanes (this does not include OOP alerts) and scenarios where the LV was determined to have remained in path but was accelerating or at traveling at constant speed. For each of these, the increase in response time was a little over 0.05s per 10m additional following distance. Finally, the pattern of the setting by alert type interaction was such that in the Off setting, where drivers do not receive alerts, drivers who select beeps (primarily Equinox drivers) respond 0.11s more slowly than drivers who select SAS. Since these drivers do not receive warnings at all, the difference may be due to demographic factors (as well as possible vehicle-related factors discussed above). In all other conditions, response to beeps is faster than response to SAS warnings (Far: 05s faster for beeps; Medium: 0.04s; Near: 0.08s).

To focus on the two key in-path scenarios, a second model of log-PABT was run including only alerts in the two scenarios in which the lead vehicle was stopped or slowing and remained throughout the 4-sec post-alert period (Approaching Slowing Vehicle and Approach Stopped Vehicle). The modeling process and predictors considered were otherwise the same as the "all-scenario" model. Model predictors and significance tests are detailed in Appendix C. Relative to the more comprehensive model, the effects of speed at event, wiper, HUD and alert type are no longer significant. Scenario is also not in the model, but with only two scenarios and the vast majority of observations in the LV slowing scenario, this is not surprising. Remaining effects (significant in both models) are the main effects of setting, night/day, and vehicle model and the interaction between following distance and road type.

Table 19 shows the least squares mean PABT for the three significant main effects. As with the analysis of all scenarios, Equinox drivers responded fastest, followed by SRX and then XTS drivers. The difference between Equinox and XTS mean response time is 0.06 sec. (Again, the reader should be reminded this could be due to vehicle-related factors.) Responses at night are 0.09 seconds slower, and drivers who use the Off setting respond 0.08 seconds more slowly than those who use Far. Responses on the Medium setting are fastest at 0.03 sec faster than Near and 0.04 sec faster than Off. The following distance by road type interaction resulted in a somewhat different pattern than previously. Here, the main effects of both road type and following distance are not significant. However, for minor arterials longer following distances are associated with longer response times (similar to the previous pattern), but for principal arterials, the pattern is reversed. Longer following distances are associated with shorter response times. The magnitude of these effects depends on the specific following distance, but a 10-meter increase in following results in a decrease of approximately 0.05 sec on principal arterials and an increase of approximately 0.08 sec on minor arterials.

Table 19 Least squares means for main effects in PABT model restricted to LV in-path slowing or stopped scenarios

Effect	Level	Mean PABT (s)
Vehicle Model*	SRX	0.741
	XTS	0.790
	Equinox	0.731
Time of Day	Night	0.811
	Day	0.701
Setting	Medium	0.709
	Near	0.737
	Off	0.827
	Far	0.747

Note: * Effect may be due to vehicle differences with respect to alert timing experienced by driver.

A follow-up analysis of PABT focused on Off versus On (Far, Medium, or Near settings) was conducted to understand differences in response associated with experiencing the FCA imminent alert (or not). Using only alerts in the FCA scenarios in which there was an in-path vehicle slowing or stopping, we modeled PABT with a linear mixed model. Setting (on versus off), road type, vehicle model, time of day, and the following distance by road type interactions were significant.

The effect of setting indicated that after adjusting for other factors, those with the system off responded 0.11s later than those with the system on. During the day, drivers responded 0.14s faster than at night (across settings), and driver response was slightly slower for the XTS compared to the other two vehicles. The road type by following distance interaction was significant and suggested that as following distance at alert increases, PABT decreases. However, the effect was only seen on interstates and principal arterials.

Average deceleration was analyzed in the same way as log PABT, using the same set of FCA imminent alert cases (e.g., driver's foot was on the accelerator at the time of the alert) and initial predictors. Significant effects include setting, road type, response scenario, vehicle model, following distance, age, wiper state, and speed at alert. Scenario interacted with setting, following distance, speed at alert, wiper, and road type. HUD, safety alert seat, odometer and gender were not significant.

The pattern of the setting by scenario interaction is shown in Figure 25. The substantial main effect of scenario is evident such that for all settings, average deceleration in LV stopped and decelerating scenarios is greatest (most negative). Within scenarios, the pattern of deceleration across setting varies. For LV decelerating and stopped the Near and Medium settings produce the largest decelerations. Far and Off are equal in the LV stopped scenario and Far averages slightly greater deceleration in the LV decelerating scenario. In the four LV not-in-path scenarios, the Near setting produces the smallest deceleration and Far and Off settings have the largest average deceleration. However, average deceleration in all of these conditions is mild (< -0.5 m/s^2 or -0.05g).

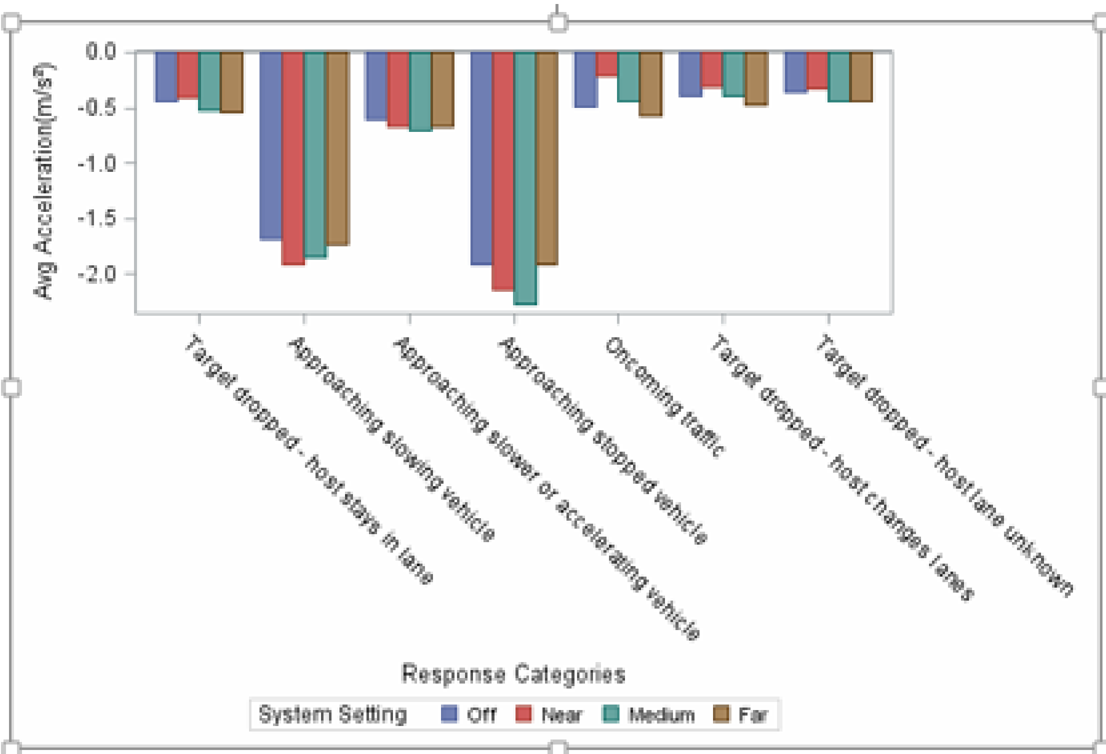

Figure 25. Interaction between scenario and setting for post-FCA alert average deceleration (m/s^2) (1g=9.8 m/s^2)

Equinox drivers decelerate more than SRX (0.05 m/s^2 less than Equinox) and XTS drivers (0.07 m/s^2 less than Equinox). The age effect indicates a 0.02 m/s^2 increase in post-alert deceleration (i.e., more negative values) per decade of age.

As with PABT, we re-ran the models using only alerts from the two key in-path scenarios: Approaching Slowing Vehicle and Approaching Stopped Vehicle. The same set of initial predictors was used, but in this analysis there are fewer significant predictors. This is due both to the reduced sample size and the simplification of scenarios. In particular, there are only two remaining interactions with scenario (suggesting that these two scenarios are more similar to each other than the larger group of scenarios).

Significant predictors include setting, road type, scenario, vehicle model, following distance, age, wiper, and average speed. The remaining interactions were scenario X following distance and scenario X speed at alert. The Near setting resulted in the highest average deceleration ($\bar{x}$=-2.66 m/s^2), following by Medium ($\bar{x}$=-2.58 m/s^2), Far ($\bar{x}$=-2.45 m/s^2), and Off ($\bar{x}$=-2.47 m/s^2). Deceleration was stronger (by -0.12m/s^2 or -0.012g) when the wipers were on. Deceleration responses by Equinox drivers were -0.03 m/s^2 greater (stronger deceleration) than the Cadillac drivers. For road type, Interstates and Principle Arterials (Freeways) produced the least severe average deceleration compared to more minor roads.

Both speed at alert and following distance interacted with scenario. For the LV stopped condition each additional 10 meters of following distance predicts 0.3 m/s^2 lighter deceleration, and each additional 10 mph of speed at alert predicts 2.6 m/s^2 stronger average deceleration. In contrast, for the LV slowing condition, 10 meters of additional following distance is associated with 0.20 m/s^2 stronger deceleration, and 10 mph additional speed at alert is associated with 0.13 m/s^2 stronger deceleration.

Finally, post-alert response to FCA was analyzed in terms of the extent to which drivers did not brake after the alert. To remind the reader, post-alert braking response was categorized as "non-response" when the driver did not brake within 3 s after the alert and "response" otherwise. Furthermore, only cases where the driver was on the accelerator at the time of the alert and did not brake in less than 0.4s after the alert were analyzed. In addition, only the Far, Medium and Near settings were analyzed because the driver did not experience the alerts in the Off setting.

Logistic regression was used to model probability of driver non-response as a function of predictors. The same set of initial factors was used for model development, and the resulting model terms include setting following distance, road type, HUD, night, vehicle model, and LV state. Age, gender, speed at alert, wiper and SAS were not significant. Following distance interacted with road type. Scenario was reduced to five based on the behavior of the LV. These categories and their non-response rates are oncoming or OOP alert (66% non-response), slowing in-path (19%), stopped in-path (24%), accelerating or constant-speed in-path (54%) and all others (81%). Non-response was least likely in the Far setting, with a 14 percent reduction in odds of non-response compared to Medium and 36 percent reduction in odds of non-response compared to Near. Drivers with the HUD On had a 15 percent greater odds of non-response than those without the HUD. Drivers were less likely to respond during the daytime (32% higher odds of non-response during the day). Finally, greater following distance at the time of the alert predicted greater non-response, but the effect was strongest on interstates and principal arterials. An increase of 10 m following distance was associated with a 26 percent increase in odds of non-response on Interstates, a 19 percent increase on Principal Arterials (Freeways), and an 8 percent increase in the remaining road types.

Adaptation

Investigation of changes over time (adaptation) focuses on using odometer as a predictor. The analyses in the previous section included odometer as a potential predictor, and these results were reported there. However, this section looks at additional changes over time.

One way in which adaptation might be observed is through changes in normal driving habits over time. To evaluate this, the following normal driving statistics were aggregated over one-month periods and modeled:

- Proportion of time over left lane boundary,
- Proportion of time over right lane boundary, and
- Average follow distance when following.

The proportions were modeled using mixed effects models with a beta distribution function, while average following distance was modeled using linear mixed models. In additional to demographic predictors, the proportion of time spent using each of the settings (calculated by number of dominant trips divided by total trips) was also used as a predictor.

After removal of non-significant predictors, the model of average following distance includes log odometer, setting, average following distance at start of study, SAS availability, age, and the log-odometer by starting following distance interaction. Individuals who turned the system off have a 0.5 m smaller (or closer) average following distance than those who leave the system on (in any setting). Vehicles equipped with the safety alert seat (SRX and XTS) available tended to follow an average of 0.89 m more closely than those without. Older drivers tend to allow a greater average following distance than younger drivers (about 1 m longer average following distance per decade of age). Finally, the starting average following distance by odometer interaction is illustrated in Figure 26 (Equinox) and Figure 27 (Cadillacs). The two patterns are very similar, but vary slightly because of the effect of SAS-availability, which applies only to the Cadillacs. At low odometer settings, there is greater divergence in following distance among drivers in this study. However, over time, drivers converge to more similar following distances. Those who follow more closely at the start still follow more closely at the end (but by a smaller margin), and those who have the system disabled follow slightly more closely than those who have the system enabled (i.e., the setting main effect).

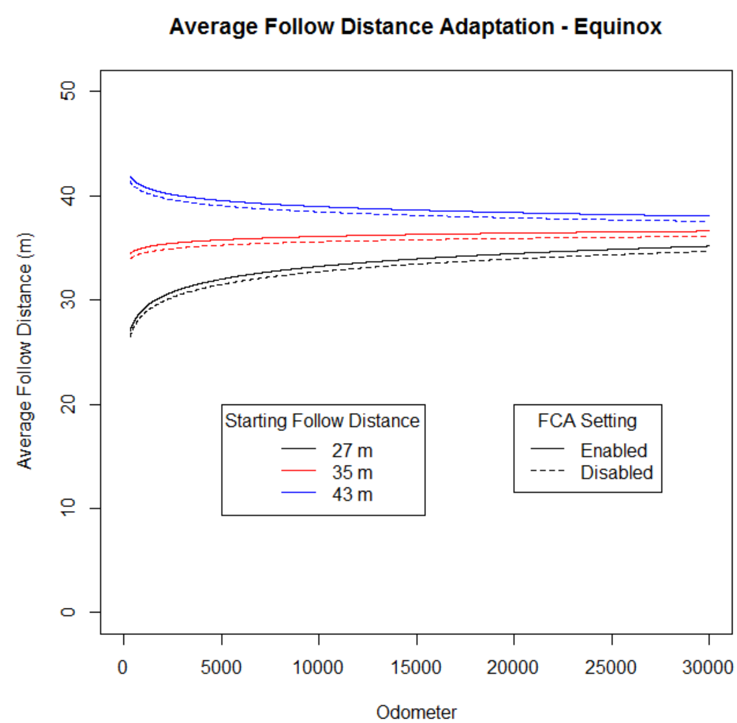

Figure 26. Model of following distance as a function of starting following distance and setting for the Equinox. Three examples of starting following distance are shown for illustration.

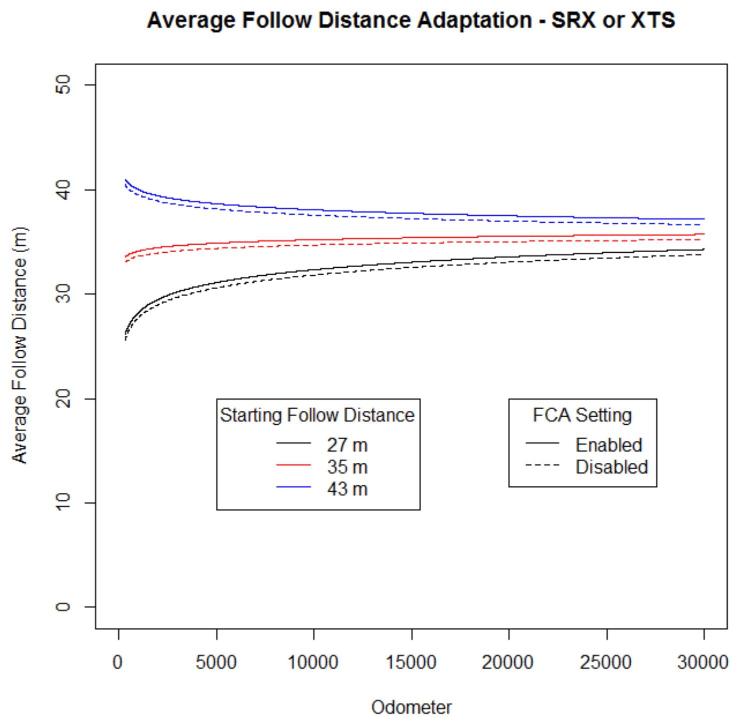

Figure 27. Model of following distance as a function of starting following distance and setting for the Cadillac SRX and XTS. Three examples of starting following distance are shown for illustration.

For the model of proportion of time over the left lane boundary, significant predictors remaining in the model include log odometer, the proportion of total driving time the system is turned off, vehicle model, age, gender, and the proportion of time over the left lane at the start of the study (averaged over the first month of observation). There were also two interactions: log-odometer X initial time over left lane, log-odometer X proportion of time in Off setting, and proportion of time in Off setting X vehicle model. It should be noted that within any given month, 80 percent of drivers have the system always Off or always On. These are represented in the proportion-time-Off variable as 1 (always Off) or 0 (always On). Drivers who switch have proportion-time-Off values between 0 and 1.

The effect of age was to predict a lower proportion over the left-lane boundary by about 5.5 percent per additional decade of age. For example, a 60-year-old driver will tend to spend about 5.5 percent less time over the left lane than a 50-year-old driver. The gender effect predicts that male drivers spend about 5 percent more time over the left lane boundary than females.

The pattern of results for the odometer, starting proportion over left lane, proportion-time-off predictors are shown in Figure 28 (Equinox), Figure 29 (SRX), and Figure 30 (XTS). Starting over-left-lane proportion and proportion Off setting are continuous predictors (along with odometer). Thus, the effects are illustrated with a set of sample values. The solid lines are drivers who have the system enabled 100 percent of the time and the dotted lines are drivers who have the system disabled 100 percent of the time. Starting over-left-lane proportions of 0 percent, 4 percent and 8 percent are shown in black, red, and blue, respectively. It should be emphasized that starting over-left-lane values in the model can occur at a variety of odometer readings. That is, the starting value is measured when each driver enters the study, not at an odometer of 0. The graphs essentially extrapolate backwards so that the value of starting over-lane proportion is not the same as the predicted value over over-lane proportion at 0 odometer.

For the all vehicles, over-left-lane proportion converged over odometer to a smaller range of values than are observed at low odometer readings. In addition, those who have the system disabled tend to have a higher proportion of over-left-lane time at low odometer readings. For the Equinox, this difference remains throughout the odometer range. The remaining differences among drivers are explained by starting over-left-lane proportion, indicative of a driving style that is eventually not related to setting choice.

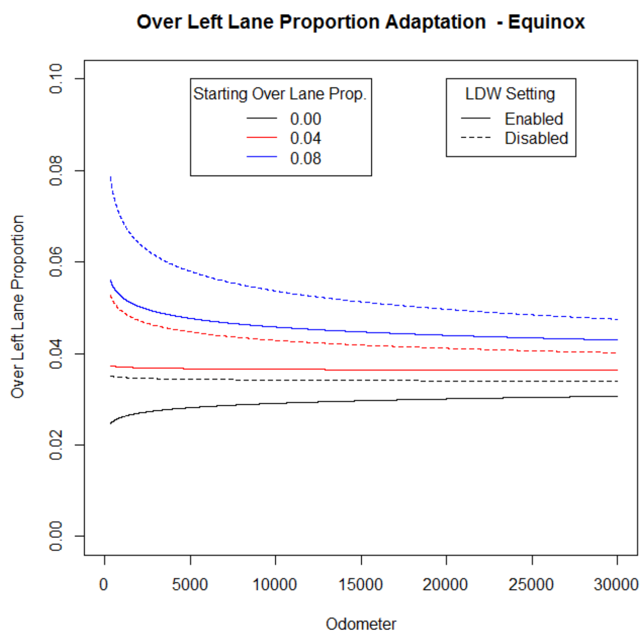

Figure 28. Model of time spent over the left lane as a function of starting tendency to be over the left lane and setting for the Equinox. Three examples of starting proportion over left lane are shown for illustration.

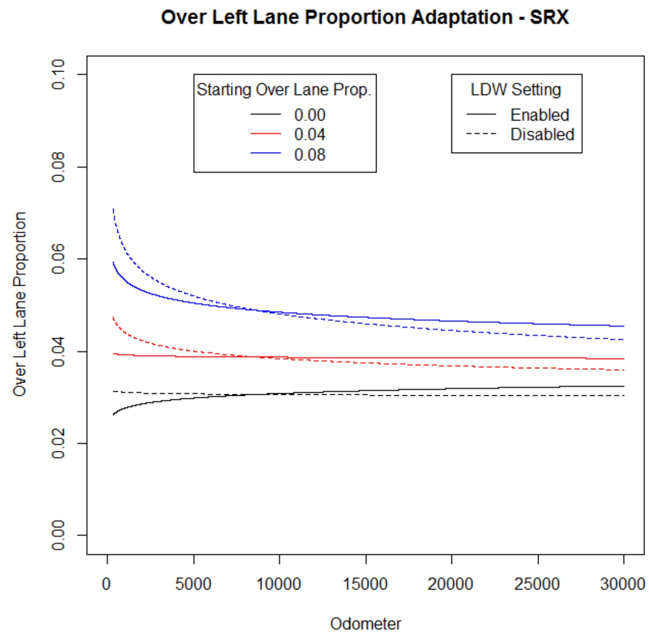

Figure 29. Model of time spent over the left lane as a function of starting tendency to be over the left lane and setting for the SRX. Three examples of starting proportion over left lane are shown for illustration.

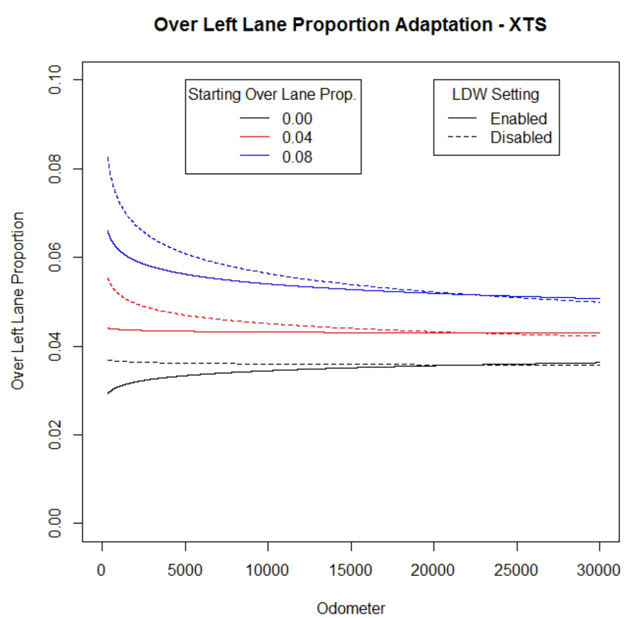

Figure 30. Model of time spent over the left lane as a function of starting tendency to be over the left lane and setting for the XTS. Three examples of starting proportion over left lane are shown for illustration.

A similar model was developed for the proportion of time spent over the right lane boundary. Since the right lane boundary is often near the road edge, whereas the left lane boundary is either a centerline or lane line, the two were not combined in analysis. The same set of starting predictors and the same modeling approach used in the previous analysis was used for the right-lane-boundary model. The right-lane model was somewhat simpler than the left-lane model. Significant predictors were log odometer, proportion of time with the LDW system Off, starting (first month of observation) proportion of time over the right-lane boundary, SAS-available (i.e., Cadillacs), and age. Interaction terms were also included for log-odometer X proportion in Off setting, log-odometer X starting over-right-lane proportion, and proportion in Off X SAS-available.

The age effect for over-right-lane proportion also indicated a reduction in over-lane proportion with age. The effect size is about half that of over-left-lane, predicting a reduction in proportion of time over right-lane boundary of about 2.5 percent per decade of age. All other effects are illustrated in Figure 31 (Equinox) and Figure 32 (SRX and XTS).

The patterns for right-lane boundary are similar to that of left-lane. Drivers with relatively higher starting over-lane proportions tend to reduce their over-lane proportion over time, whereas those with lower proportions tend to increase over time. The result is less between-driver variation at larger odometer readings compared to smaller ones. For Equinox, drivers who have the system Off tend to spend less time over the right-lane boundary. Although Cadillac drivers show the same trend, this difference is substantially reduced. It is also worth, more generally, that drivers generally spend more time over the right-lane boundary compared to the left-lane boundary. Thus, selected starting values for right-lane proportion are larger to illustrate a representative range of values.

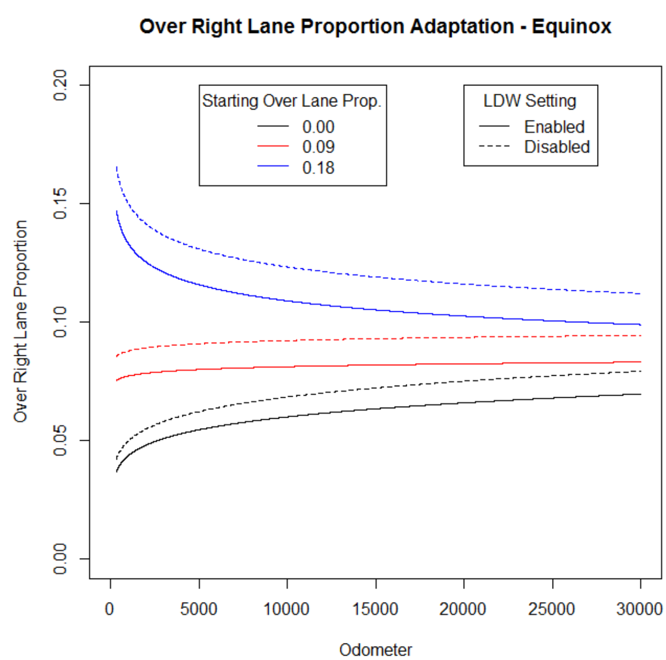

Figure 31. Model of time spent over the right lane as a function of starting tendency to be over the right lane and setting for the Equinox. Three examples of starting proportion over right lane are shown for illustration.

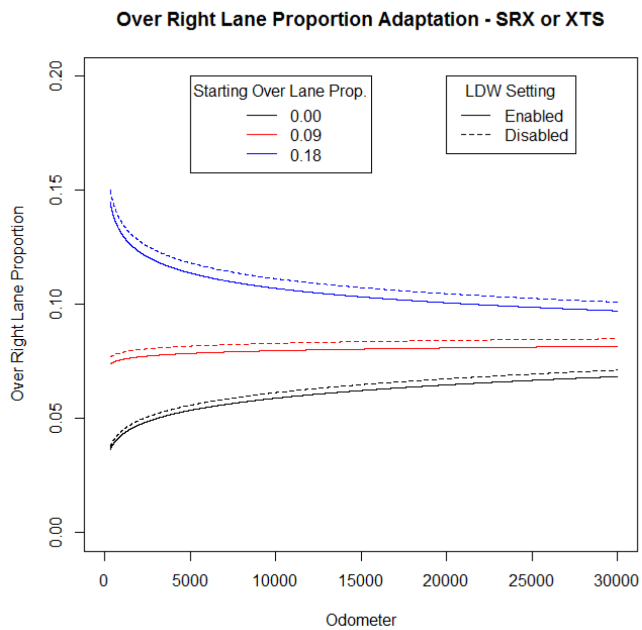

Figure 32. Model of time spent over the right lane as a function of starting tendency to be over the right lane and setting for the Cadillacs. Three examples of starting proportion over right lane are shown for illustration.

Summary and Discussion

This field study used an innovative large-scale data collection technique to gather information about how crash avoidance systems operate in the field and how drivers respond to them. Although the specific systems studied were the GM camera-based FCA and LDW systems, this technique could be readily applied to other emerging active safety systems and used to better inform emerging active safety consumer metrics. It should be noted that both the FCA and LDW systems evaluated have consistently met the Crash Avoidance New Car Assessment Program (CA NCAP) performance requirements since this Program was initiated.

The telematics-based data collection technique employed harnessed the unique and powerful telematics capabilities of OnStar coupled with a production crash avoidance module (i.e., the Front Camera Module) that was specifically designed to support the type of active safety system data collection described in this paper focused on gathering key, high-priority numeric data. In this study, 1,958 consenting owners of model year 13 Chevrolet Equinox, Cadillac SRX, and Cadillac XTS vehicles equipped with the FCA and LDW systems provided data on alert events and driving exposure over the course of about 1 year. Beyond the sheer amount of active safety system data collected, the geographic span of the data collected via this remote data collection approach was also unprecedented, as vehicles from 48 of the 50 States in the United States were represented in this effort.

Data analysis was enhanced using existing highly detailed field operational test data (e.g., forward looking video) at UMTRI. Thus, targeted, large-sample data collection, combined with information from highly detailed data, were used together to develop an efficient way to understand the performance of two active safety systems currently included in the NCAP Program.

Two general types of data were collected in the current study: (1) "snapshots" of kinematic and other variables 3-6 seconds before, at, and 4 seconds after either FCA imminent crash or LDW alert events, and (2) histograms of driving data to provide information about exposure and normal driving. In addition, the time of braking onset after the alert (within 4 sec of the alert) was recorded. Overall, this data was used to answer questions in several broad research categories: system availability, alert rates, driver acceptance (e.g., on/off setting choices), driver response to alerts, and driver adaptation over time.

Data analysis was enhanced by using highly detailed "traditional" field operational test data previously gathered by UMTRI, as part of the NHTSA-sponsored Advanced Collision Avoidance Study (ACAS) FOT and FHWA-sponsored Safety Pilot efforts. These data provided an extensive set of multi-channel video and continuously measured kinematic information, which was coupled with the current targeted, large-sample data collection, to develop an entirely new and efficient way to understand the field performance of two active safety systems. These previous FOT datasets were invaluable in developing some key algorithms to aid in understanding the data patterns observed with the more limited numeric data gathered in the present study.

Based on work conducted under the ACAS FOT, FCA imminent alerts were classified into scenarios to better understand system performance and driver behavior. We developed seven scenarios based on our determination using the available data of whether the LV stayed in path 4 seconds after the alert, the longitudinal movement state of the LV, and whether the HV steered or not. The seven scenarios, as well as the estimated corresponding percentages of FCA imminent alerts observed in each of these scenarios, which total up to 100 percent, are shown below.

1. Approaching slowing vehicle (19% of alerts)
2. Approaching stopped vehicle (0.4%)
3. Approaching slower or accelerating vehicle (31%)
4. Oncoming traffic (considered out-of-path false alerts) (2%)
5. Target dropped - host changes lanes (11%)
6. Target dropped - host stays in lane (16%)
7. Target dropped - host lane unknown (20%)

These scenario classification definitions were used throughout FCA analysis to understand context surrounding FCA imminent alerts. The first two scenarios shown above are considered key scenarios for preventing rear-end crashes (though it should noted that the second "Lead Vehicle Stopped" scenario rarely occurred). The remaining scenarios can typically be resolved with minimal driver response. At a high level, observed driver responses were consistent with expected responses for these scenarios (e.g., higher decelerations were observed when approaching a slowing or stopped vehicle).

The availability of the systems were evaluated as a portion of the time the system would be expected to be available based on the LDW (above 35 mph) and FCA (above 25 mph) minimum operating speeds. LDW system availability was primarily driven by lane confidence, whereas FCA system availability above was primarily driven by the presence of a detected lead vehicle. Based on system-determined reasons for unavailability, weather and poor visibility occurred substantially less than 1 percent of the driving time.

Driver behavior surrounding alerts was investigated in several ways. The On/Off setting choice can be thought of as the most fundamental and primary measure of driver acceptance, which interacted in important ways with the alert type setting. For both LDW and FCA, the Cadillac SRX and Cadillac XTS drivers had the option of choosing between warning beeps or haptic seat vibration pulses (referred to by GM as the safety alert seat), which applied to both systems.

Cadillac drivers selected the safety alert seat (over beeps) 90 percent of the time, and when the haptic seat was turned on, the LDW system off time was 38 percent. For Chevrolet Equinox drivers, who only had the beeps option, the corresponding LDW off time nearly doubled increasing to 71 percent. More generally, the LDW Off time increased until leveling off at about 10,000 miles (approximately one year of driving). At that point, drivers generally settled on whether they left the system on or off. Drivers who drove more miles per month (1 sd above the mean monthly mileage) also had over 40 percent greater odds of system deactivation. In addition, Equinox drivers who spent more time driving over the right lane boundary or who drove more in the 35- to 55 mph speed range tended to turn the system off more.

For FCA, there were four setting choices (Far, Medium, and Near alert timing, as well as an Off setting). Overall, system off time was considerably lower for FCA than LDW, and alert type impacted off time in a similar fashion. When the safety alert seat was selected (rather than beeps) by Cadillac drivers, FCA system off time was 6 percent. For Equinox drivers (who only had beeps option), the corresponding FCA off time nearly tripled to 17 percent. Together with the LDW results reported above, these results clearly suggest the safety alert seat increases driver acceptance of both LDW and FCA systems, which is further supported by the increased use of the FCA Far alert time setting for Cadillac Safety Alert users (72%) relative to Equinox (49%) beeps users. The Far setting was the most common setting observed across vehicles, followed by Medium and then Near. In general, drivers started out using the Far setting, explored other settings (generally from 5,000-25,000 miles), and then returned to the Far setting. Use of the Off setting also decreased with age.

Driver response to FCA imminent alerts was measured in three ways. First, post-alert braking time (PABT) was defined as the time between the alert and initial brake onset for cases where the driver's foot was on the accelerator at the time of the alert (eliminating PABTs either below 0.4 sec or above 3 seconds). Second, using these same cases, average deceleration was defined as the speed reduction between the alert and 4 seconds after the alert, divided by the 4-second time interval. A third driver response measure focused on non-response, defined as the lack of any braking occurring between 0.4 and 3 seconds after the alert. These driver response measures were evaluated as a function of odometer (experience/time) and FCA scenario, and additional analysis focused on addressing the two key FCA in-path scenarios (e.g., lead vehicle slowing or stopped), where substantially higher decelerations were observed (discussed further below).

PABT was affected by a number of factors, with FCA setting, following distance at alert, weather (wiper on/off), time of day (day/night), speed at alert, and having the most significant effects. Drivers were 0.11s slower with the system Off compared to Far (which used the same alerting algorithm to record phantom alerts not presented to the driver). The corresponding difference was 0.07s for the two key in-path FCA scenarios. For context, a vehicle travels about 1 ft per 10 mph in 0.07s (e.g., 7 ft at 70 mph, 6 ft at 60 mph). Responses were about 0.13s slower for every 10 mph increase in speed at alert and about 0.05s slower for every 10m increase in following distance at alert. In poor weather conditions (wipers on), responses were 0.07s slower to all scenarios and 0.11s slower in the two key scenarios, compared to when wipers were off. The same effect sizes were seen for night versus day. Thus, in conditions of poorer visibility, braking responses were slower.

For driver braking (average acceleration) levels following an alert, alert scenario was the strongest predictor. Although this scenario effect interacted with both following distance and vehicle speed, in general, the two key in-path alert scenarios resulted in much greater deceleration (averaging approximately 2.0m/s^2 or 0.20 g) than the remaining scenarios (averaging below 0.5 m/s^2 or 0.05 g). For these scenarios, setting was a significant predictor of average deceleration, but observed differences were a relatively small 0.2 m/s^2 between settings. Consistent with the observed PABT data, poor visibility (having the wipers on) led to stronger average decelerations (0.12 m/s^2 higher). For the lead vehicle stopped FCA scenario, every 10 mph increase in speed at alert resulted in 2.6 m/s^2 higher average deceleration levels, whereas for the LV braking scenario, every 10 mph increase in speed at alert resulted in 0.13 m/s^2 higher average deceleration levels.

Driver non-response levels are shown below for the FCA scenarios identified.

1. Approaching slowing vehicle (19%)
2. Approaching stopped vehicle (24%)
3. Approaching vehicle moving at slower (but not braking) or accelerating (54%)
4. Oncoming traffic (considered out-of-path false alerts) (66%)
5. Remaining scenarios (target lost after 4 sec) (81%)

Thus, the driver non-response levels were highest for conditions in which the lead vehicle was estimated to be not present 4 seconds after the alert, or when present but accelerating at the 4 sec post-alert time. In some cases of non-response for these two conditions, the driver may have coasted rather than braking to manage the situation.

Overall, system alert rates were higher when the system was off relative to a matched system-on condition (i.e., for LDW the On setting, for FCA the Far alert timing setting), and LDW alerts occurred markedly more often than either FCA headway or FCA imminent alerts. Median LDW alert, FCA headway alert, and FCA imminent alert rates (per 100 miles) were 29 percent, 18 percent, and 19 percent higher when the crash avoidance system was OFF rather than ON. Median LDW alert rates for the On and Off setting were 37.4 and 48.4 per 100 miles respectively. Median FCA headway alert rates for the Off, Far, Medium, and Near settings were 9.6, 8.1, 2.4, and 0.17 per 100 miles respectively. Median FCA imminent alert rates for the Off, Far, Medium, and Near settings were 1.3, 1.1, 0.75, and 0.54 per 100 miles respectively. (Note that the pattern of decreasing FCA alert rates as alert timing increases from Near to Far setting is expected based on the FCA alert timing algorithms.)

Relative to previous traditional active safety FOT efforts, one of the particular strengths of this study was the ability to look at changes in data patterns over a considerably longer period (e.g., about 1 year instead of 6 weeks) for a larger sample of drivers (e.g., 2,000 instead of 100). Overall, there was no substantial evidence of unintended consequences due to driver adaptation. As odometer (and hence time) increased, whether or not the system was turned on, alerts rates went up for LDW and down for FCA, with the FCA reduction dependent on the estimated FCA scenarios. As would be expected, oncoming vehicle (out-of-path) alert rates did not change over time, since these alerts are largely out of the driver’s control. In contrast, alerts to lead vehicles that are accelerating or stopped, and alerts where the lead vehicle was lost but the host vehicle did not change lanes or the driver’s lane position was unknown decreased the most. These could be argued to be scenarios that the driver can anticipate and perhaps can adapt to avoid setting off the FCA. In the two key in-path FCA scenarios described above (where a lead vehicle remaining present), alert rates decreased somewhat as odometer increased.

Finally, changes in normal driving behavior over time (odometer) was examined in terms of following distance and time spent over the left lane and right lane boundaries. Overall, drivers who started with more extreme following distances (short or long, relative to other drivers) or percent of time spent over either lane boundary tended to become more like an average driver over time. This suggests an effect of getting used to the vehicle rather than an effect of the system itself.

In summary, this new telematics-based, large-scale OnStar data collection technique has several distinct strengths for evaluating active safety systems, including cost, sample size, drivers using their own vehicles where they can turn systems off, ability to look at long-term effects, data efficiency, and the ability to get “rapid-turnaround” large-scale results. Since this technique currently focuses on key high-priority numeric data, it complements and benefits from the extensive set of multi-channel video and continuously measured kinematic information gathered in “traditional” FOTs. This new type of telematics-based data collection appears ideally suited for understanding the safety impacts of active safety (crash avoidance) systems that are rapidly emerging globally.

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Appendix A Data Collection

Types of Collected Data

Two types of data were collected for each ignition cycle (or trip) from each vehicle: the alert-triggered data and trip-aggregated statistics data.

The alert-triggered data contain a wide range of information describing alert situations such as kinematics of the subject vehicle and lead vehicle, safety system settings, pedal positions, lane position, and lead vehicle type. The alert-triggered data were sampled at three discrete time points, 3-6 s prior to the alert event, at the alert time, and 4 s after the alert time. The varying time difference between the pre-alert and alert times was due to the update timings of two buffers which temporarily held data as potential pre-alert data. Each buffer was updated every 6 s with an offset of 3 s from the other buffer, and the pre-alert data were obtained from the one carrying the older data to avoid missing data during the updating process. The alert-triggered data also contained the information of driver response to an alert signal (e.g., brake initiation), which occurred between the alert and post-alert times such as brake. There are maximum numbers of alerts that can be recorded in each trip (three for FCA imminent alert events and five for LDW alert events). The alert queue was created based on the First-In, First-Out (FIFO) method, and therefore only the newest alerts were stored if the number of alerts exceeded the maximum allowed.

The trip-aggregated statistics data are comprised of two types of data: periodic counters and event-based counters. The periodic counters represent durations of particular states in a single ignition cycle, e.g., vehicle speed, system settings, lane offset and others. These counters were incremented by one at 1 Hz of sampling rate. Some groups of the periodic counters form histograms, e.g., durations of time for vehicle speed in different speed ranges under certain conditions. On the other hand, the event-based counters represent the numbers of occurrences of discrete events, e.g., number of alerts.

Data Delivery and Processing

Both of the alert-triggered data and trip-aggregated statistics data were temporarily stored in each vehicle in internal memory in the FCM. In about every four ignition cycles, those data were wirelessly transferred to the OnStar server when the ignition was turned on. The collected data were delivered online to UMTRI typically four times a day at 12 A.M., 6 A.M., 12 p.m., and 6 p.m. in the comma-separated value (csv) format. The delivered data was parsed and stored in a relational database in Microsoft SQL Server on an UMTRI server.

Collected Data Used to Support Data Analysis

The database contains three main tables for the analyses: TTripStats, TAlerts, and TCounters, which contain trip summary data, the alert-triggered data, and the trip-aggregated statistics data, respectively. These tables also contain additional variables that were derived from the original data such as time of day, which was converted from Greenwich Mean Time (GMT) converted to the local time. Detailed descriptions for these tables are provided in the tables below.

In these tables, the single star (*) indicates that the data was used only in the initial data processing. Derived data is indicated by a (D).

Summary Table (TTripStats)

Table 20 Data in TTripStats

Field name	Description	Unit
FileID	File ID in the order of file delivery to UMTRI	-
RowInFile (*)	Row number to specify the data location in the original data file	-
VehicleID	Anonymized vehicle ID	-
TripStart	Trip start time in Greenwich Mean Time (GMT)	date/time
TripEnd	Trip end time in GMT	date/time
StartOdo	Odometer value at TripStart	km
EndOdo	Odometer value at TripEnd	km
cnt_total	Duration of trip from the Trip Statistics table	s
DurationSeconds (D)	Duration of trip (difference between TripStart and TripEnd)	s
InvalidCode (D)	Validity type	-
EndSunElevation (D)	Sun elevation relative to the vehicle position at TripEnd	deg
StartTimeZone (D)	Local time zone at TripStart: Alaska, Central, Eastern, Hawaii-Aleutian, Mountain, or Pacific	-
StartGMT_OFFSET (*) (D)	Offset of local time from GMT at TripStart during regular (non-daylight saving) time period	hour
StartGMT_DST_OF (*)(D)	Offset of local time from GMT at TripStart during daylight saving time period	hour
StartLocalTimeOfDay (D)	Local start time adjusted from TripStart using StartGMT_OFFSET or StartGMT_DST_OF	date/time
EndTimeZone (D)	Local time zone at TripEnd: Alaska, Central, Eastern, Hawaii-Aleutian, Mountain, or Pacific	-
EndGMT_OFFSET (*)(D)	Offset of local time from GMT at TripEnd during regular (non-daylight saving) time period	hour
EndGMT_DST_OF (*)(D)	Offset of local time from GMT at TripEnd during daylight saving time	hour
EndLocalTimeOfDay (D)	Local start time adjusted from TripEnd using EndGMT_OFFSET or EndGMT_DST_OF	date/time

Alert Event Table (TAlerts)

Table 21 shows a list of variables which provides summary information of alerts available in TAlerts, and Table 22 contains the rest of the variables in TAlerts to represent the driving situation in detail at the distinct time points around the alert time. In the TAlerts table, each row corresponds to a single alert, and therefore multiple rows can be associated with the same trip.

Table 21 Summary of alert events

Field name	Description	Unit
VehicleID	Anonymized vehicle ID	-
TripStart	Trip start time in GMT	date/time
TripEnd	Trip end time in GMT	date/time
StartOdo	Odometer value at trip start	km

Field name	Description	Unit
EndOdo	Odometer value at trip end	km
InvalidCode (D)	Validity type	-
FileID	File ID in the order of file delivery to UMTRI	-
RowInFile (*)	Row number to specify the data location in the .csv file	-
	Number of alerts that occur in a proximity in the last 4 weeks	-
AlertTime (*)	Time of alert in GMT	data/time
LocalTimeOfDay (D)	Time of alert in local time	data/time
F_SYSTEM (D)	Functional System classifying into road type	-
	Distance between the locations at TripStart and AlertTime	mile
SunElevation (D)	Sun elevation relative to the vehicle location at alert time	deg
SunAzimuth (D)	Sun azimuth relative to the vehicle heading at alert time	deg
TimeZone (D)	Local time zone at alert time: Alaska, Central, Eastern, Hawaii-Aleutian, Mountain, or Pacific	-
GMT_OFFSET (*)(D)	Offset of local time from GMT at alert time during regular (non-daylight saving) time period	hour
GMT_DST_OF (*)(D)	Offset of local time from GMT at alert time during daylight saving time period	hour
Hit_Miss	Distance between the alert location and the closest polyline in the road data	m
VehicleID	Version of road data used in the GIS analysis	year
TripStart	Annual average daily traffic	-
TripEnd	Length of the road segment in the road data in which an alert occurred	mile
StartOdo	Vehicle miles traveled in a specified road segment	mile
EndOdo	Flag to indicate if a road segment associated with an alert is found within the tolerance range	-

Table 22 Detailed information of alert events

Field name	Sampling time	Description	Unit
Timer	Pre, Alert & Post	Time showing age of trip	s
AlertWarning	Pre, Alert & Post	FCA state (0: No alert, 1: Reserved, 2: Headway alert, 3: Imminent alert)	-
LdwLocation	Pre, Alert & Post	LDW state (0: No alert, 1: Left, 2: Right)	-
AvgSpeed	Pre, Alert & Post	Vehicle speed	km/h
AccelPosition	Pre, Alert & Post	Accelerator position	-
BrakePedalInitial	Pre, Alert	Driver brake switch (onset flag)	-

Field name	Sampling time	Description	Unit
BrakePosition	Pre, Alert	Driver brake position (0-100)	-
TurnSignal	Pre, Alert & Post	Turn signal status (0: Off, 1: Left, 2: Right)	-
FollowDistance	Pre, Alert & Post	Range to target	m
LeftLanePos	Pre, Alert & Post	Left lane position	m
RightLanePos	Pre, Alert & Post	Right lane position	m
LeftLaneConf	Pre, Alert & Post	Left lane tracking confidence (0: Low1, 1: Low2, 2: Medium, 3: High)	-
RightLaneConf	Pre, Alert & Post	Right lane tracking confidence (0: Low1, 1: Low2, 2: Medium, 3: High)	-
Hours (*)	Alert Only	GPS time (hours)	hour
Minutes (*)	Alert Only	GPS time (minutes)	min
Seconds (*)	Alert Only	GPS time (seconds)	s
HoursValid (*)	Alert Only	GPS time validity (hours)	-
MinutesValid (*)	Alert Only	GPS time validity (minutes)	-
SecondsValid (*)	Alert Only	GPS time validity (seconds)	-
Wiper	Alert Only	Wiper flag (0: Off, 1: On)	-
TimeBrkPedAchvd	During 4 s period after Alert	Time brake is activated (initial)	s

Trip Statistics Table (TCounters)

The structure of TCounters table is shown in Table 23. Since the Name field contain a large number of counters (365 in total), their corresponding values were stored in the Value field in order to avoid an overly large number of columns in the table.

Table 24 and Table 25 provide descriptions of the counters in Name for the periodic-counters and event-based counters, respectively. These counter variables include not only counters, per se, but also histograms. There are one- and two-dimensional histograms. Many counters address the time that a particular state exists, e.g., time spent within a speed bin. These counters including the histograms (counters within bins) are incremented once a second (frequency of 1 Hz). Counters addressing alert event occurrences, however, simply count the number of those events.

Since many counters are similar with slight differences, comprehensive representations are used for their names. The italic symbols, *a*, *b*, *c*, and, *d* represent the variables which take different values between a particular counter and another counter of the same kind, and the combinations of the values for the four variables are defined in the second column in the tables.

Table 23 Trip Statistics (Structure of TCounters table)

Field Name	Description	Unit
FileID	File ID in the order of file delivery to UMTRI	-
VehicleID	Anonymized vehicle ID	-
TripStart	Trip start time in Greenwich Mean Time (GMT)	date/time
TripEnd	Trip end time in GMT	date/time
StartOdo	Odometer value at TripStart	km
EndOdo	Odometer value at TripEnd	km
Name	Name of counter variables	-
ByteNum (*)	Byte location to specify a particular counter	-
Value	Value of the counter variable	-
RowInFile (*)	Row number to specify the data location in the original data file	-
InvalidCode	Validity type	-

Table 24 Counter variables in the Name field in TCounters (periodic counters or histograms)

Counter name	Description	Frequency [Hz]
cnt_v_*a*_*b*_nocipv	Histogram of duration of time without a target (closest-in-path vehicle) in host vehicle speed bins, [*a*, *b*) mph, where (*a*, *b*) ∈ {(0, 5), (5, 15), (15, 25), (25, 35), (35, 45), (45, 55), (55, 65), (65, 75), (75, 85), (85, 95), (95, 255)}	1
cnt_v_*a*_*b*_cipv	Histogram of duration of time with a target (closest-in-path vehicle) in host vehicle speed bins, [*a*, *b*) mph, where (*a*, *b*) ∈ {(0, 5), (5, 15), (15, 25), (25, 35), (35, 45), (45, 55), (55, 65), (65, 75), (75, 85), (85, 95), (95, 255)}	1
cnt_v_*a*_*b*_x_*c*_*d*	Histogram of duration of time of the target range in bins, [*c*, *d*) m, in host vehicle speed bins, [*a*, *b*) mph, for the combinations defined by the direct product, (*a*, *b*) × (*c*, *d*), where (*a*, *b*) ∈ {(0, 20), (20, 25), (25, 30), (30, 35), (35, 40), (40, 45), (45, 50), (50, 255)} and (*c*, *d*) ∈ {(0, 5), (5, 10), (10, 15), (15, 20), (20, 25), (25, 30), (30, 35), (35, 40), (40, 50), (50, 60), (60, 70), (70, 80), (80, 90), (90, 100), (100, 255)}	1
cnt_v_*a*_*b*_wiper_on	Histogram of duration of time of wiper activated in speed bins, [*a*, *b*) mph, where (*a*, *b*) ∈ {(0, 25), (25, 45), (45, 65), (65, 85), (85, 255)}	1
cnt_v_*a*_*b*_FCA_headwayalert	Histogram of duration of time of headway alert in speed bins, [*a*, *b*) mph, where (*a*, *b*) ∈ {(0, 25), (25, 45), (45, 55), (55, 65), (65, 75), (75, 85), (85, 255)}	1
cnt_vehiclesdetected_*a*	Histogram of duration of time of the number of vehicles detected, *a*, where *a* ∈ {0, 1, 2, 3, 4, 5, 6, 7}	1

Counter name	Description	Frequency [Hz]
cnt_v_*a*_*b*_leftconf_*c*	Histogram of duration of time of left lane tracking confidence at *c* in speed bins, [*a*, *b*) mph, for the combinations defined by the direct product, (*a*, *b*) × *c*, where (*a*, *b*) ∈ {(0, 25), (25, 45), (45, 55), (55, 65), (65, 75), (75, 85), (85, 255)} and *c* ∈ {0, 1, 2, 3}	1
cnt_v_*a*_*b*_rightconf_*c*	Histogram of duration of time of right lane tracking confidence at *c* in speed bins, [*a*, *b*) mph, for the combinations defined by the direct product, (*a*, *b*) × *c*, where (*a*, *b*) ∈ {(0, 25), (25, 45), (45, 55), (55, 65), (65, 75), (75, 85), (85, 255)} and *c* ∈ {0, 1, 2, 3}	1
cnt_LDW_State_*a*	Histogram of duration of time of LDW state at *a*, where *a* ∈ {'Off', 'Disabled', 'NRTA', 'RTA', 'Blocked', 'Unknown'}	1
cnt_FCA_State_*a*	Histogram of duration of time of FCA state at *a*, where *a* ∈ {'Off', 'Disabled', 'NRTA', 'RTA', 'Blocked', 'Unknown'}	1
cnt_FDI_State_*a*	Histogram of duration of time of FDI state at *a*, where *a* ∈ {'Disabled', 'NRTA', 'RTA' }	1
cnt_LDW_on	Histogram of duration of time of LDW on	1
cnt_FCA_on	Histogram of duration of time of FCA on	1
cnt_FCA_near	Histogram of duration of time of FCA Near	1
cnt_FCA_medium	Histogram of duration of time of FCA Medium	1
cnt_FCA_far	Histogram of duration of time of FCA Far	1
cnt_leftlaneoffset_*a*_*b*	Histogram of duration of time of distance between the left lane boundary and FCM camera in bins, [*a*, *b*), where (*a*, *b*) ∈ {(−1, −0.8), (−0.8, −0.6), (−0.6, −0.4), (−0.4, −0.2), (−0.2, 0), (0, 0.2), (0.2, 0.4), (0.4, 0.6), (0.6, 0.8), (0.8, 1)} m.	1
cnt_rightlaneoffset_*a*_*b*	Histogram of duration of time of distance between the right lane boundary and FCM camera in bins, [*a*, *b*), where (*a*, *b*) ∈ {(−1, −0.8), (−0.8, −0.6), (−0.6, −0.4), (−0.4, −0.2), (−0.2, 0), (0, 0.2), (0.2, 0.4), (0.4, 0.6), (0.6, 0.8), (0.8, 1)} m.	1
cnt_v_*a*_*b*_LDW_NRTA_*c*	Histogram of duration of time of LDW NRTA Bit *c* in speed bins, [*a*, *b*) mph, for the combinations defined by the direct product, (*a*, *b*) × *c*, where (*a*, *b*) ∈ {(0, 25), (25, 45), (45, 55), (55, 65), (65, 75), (75, 85), (85, 255)} and *c* ∈ {0, 1, 2, 3, 4, 5}. <u>LDW NRTA reason bit</u> 0 – speed under threshold 1 – adverse weather	1

Counter name	Description	Frequency [Hz]
	2 – low visibility 3 – left lane position invalid 4 – right lane position invalid, and 5 – single lane performance	
cnt_v_*a*_*b*_FCA_NRTA_*c* (**)	Histogram of duration of time of FCA NRTA Bit *c* in speed bins, [*a*, *b*) mph, for the combinations defined by the direct product, (*a*, *b*) × *c*, where (*a*, *b*) ∈ {(0, 25), (25, 45), (45, 55), (55, 65), (65, 75), (75, 85), (85, 255)} and *c* ∈ {0, 1, 2, 3}. FCA NRTA reason bit 0 – speed under threshold, 1 – adverse weather, 2 – low visibility, and 3 – speed above threshold (no limit for the vehicles in this study)	1
cnt_total	Duration of time of total trip length	1
cnt_chimealertselected	Duration of time of “beep” alert type setting	1
cnt_hapticalertselected	Duration of time of “seat” alert type setting	1

Table 25 Counter variables in the Name field in TCounters (event-based counters)

Counter name	Description
cnt_LDW_Left_Alert	Number of left LDW alert in a trip
cnt_LDW_Right_Alert	Number of right LDW alert in a trip
cnt_LDW-inhibit_*a*	Number of LDW inhibitions for the reason, *a*, where *a* ∈ {‘steeringwheelrate’, ‘rightturnsignalactive’, ‘leftturnsignalactive’, ‘curvecutting’, ‘brake’, ‘acceleration’, ‘any’}
cnt_FCA_headwayalert	Number of FCA headway alerts in a trip
cnt_FCA_collisionalert	Number of FCA imminent alerts in a trip
cnt_FCA_suppression_*a* (**)	Number of FCA suppressions for the reason bit, *a* = 1, 2, …, 15.

Unexpected Data Issues

Of the parsed data, some variables were unavailable, corrupted, or unsuitable for the analysis due to low resolution. Workarounds were found for some of them by fixing erroneous values or using alternative variables. If there was no workaround, relevant data were not used. A list of such data issues is shown in Table 26.

Table 26 Unexpected Data Issues Encountered

Signal	Issue	Use	Workaround Approach
FCA not ready to assist counter	False zeros	Availability	None
Invalid GPS data	Out of feasible range	Location identification	N/A
Longitudinal acceleration	No data	Characterizing conflict, driver braking response	Average acceleration from speed data
Min & max yaw rate and lateral acceleration after alert	Miscoded	Steering response, lane change	Used position in lane to predict type of steering response (lane change or not)
Odometer	Odometer decrease	Analyzing trip, computing conflict rate	N/A
Relative acceleration of forward target	Invalid values	Characterizing conflict	Average acceleration from speed data
Relative speed of forward target	Upper bits overwritten	Characterizing conflict, driver braking response	Values reconstructed
Trip duration counter	Delayed activation	Analyzing trip	N/A

Appendix B Details of Algorithms to Aid Analysis

Appendix B presents details of the analysis done with the OnStar data to derive the results presented in earlier sections of this report. The techniques and analysis approach for some of the OnStar results were validated and enhanced using other UMTRI naturalistic driving datasets that, unlike the current data set, include continuous time-series data along with time-synchronized video of the forward scene and driver/cabin environment and in some data sets, video of the space adjacent to the host vehicle on the right and left. The two primary archives used in this effort were the Automotive Collision Avoidance System (ACAS) FOT and Safety Pilot Model Deployment datasets. The ACAS FOT dataset was used because it has a detailed analysis of forward collision alert events. In this effort, trained researchers reviewed video of every FCA imminent alert to classify them into different scenarios, and similar scenarios were used in this analysis. The Safety Pilot dataset was selected because the vehicles are privately owned (like in the current study) and are equipped with a similar forward-scene ranging and lane-tracking sensor as deployed in the current study. A description of how these archives were used to support the results shown here is given below, along with details of how the OnStar data were processed to support the findings and conclusions presented in the main body of this report.

Safety Pilot Naturalistic Driving Field Operational Test Data Analysis

The Safety Pilot Model Deployment (SPMD) project was intended to explore how well connected (wireless) vehicle safety technologies and systems work in a real-life environment with real drivers using their own vehicles. Over 2800 vehicles and 29 infrastructure sites (mainly signalized intersections) were instrumented with vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) wireless technology. One hundred twenty-eight of the 2,800 vehicles had more elaborate warning systems and were instrumented with the UMTRI Data Acquisition System (DAS). The majority of these vehicles were passenger cars, although buses, tractor-semis, and motorcycles were also included in this enhanced set. The analysis below on lateral and forward conflict events is restricted to only passenger vehicles to better allow comparisons to the current study.

Data Content

To provide context to the quantity, breadth, scope of data and video collected in the Safety Pilot Model Deployment Field Operational Test (FOT—which is currently ongoing as of this report), the following subsections provides an overall summary of the naturalistic driving database from Safety Pilot, while the subsequent subsection discusses the sensors used to collect the measures (since there are similarities between the systems deployed in Safety Pilot and the production sensors and systems examined in the current study.)

<u>*Exposure Summary*</u>
Driving data collected in the SPMD falls into two broad categories, namely, V2V basic safety messages (BSMs) and the enhanced driving dataset collected by the UMTRI DAS. The BSM dataset contains time and basic GPS position information as detailed in the SAE J2735 DSRC specification. For the analysis related to the current study, only the enhanced driving database was used. A broad description and summary of the distance and time travelled, number of trips, and overall database size is given in Figure 33. Of note is the comprehensive list of measures recorded by the UMTRI DAS and described in the upper part of the figure along with the fact that as of late 2014 over 2 million miles and almost 80,000

hours of naturalistic driving are in the main SPMD database. Nominally, the time-series data in this archive is captured and stored at 10 Hz. Also of note in the figure, the database contains 25 principal tables that constitute over 18 billion records. There is over 16 terabytes of continuous video to support the objective time-series measures.

Basic Driving Database (Sent OTA BSM)—Time; GPS location and heading; Speed; Acceleration; Yaw-rate; Brake Pedal Status; Vehicle length and width

Enhanced Driving Database (UMTRI DAS)—Time; GPS location, heading, quality; Speed, Acceleration; Yaw-rate; Brake and Cruise control status; Forward object detection; Lane tracking; Inform and imminent warnings; Remote vehicle BSM and classification; Forward, cabin, rear-left, rear-right video; Triggered audio.

Summary as of November 12th, 2014

Basic Driving Database (Sent OTA BSM)

Exposure			Per Trip Average			Database and Video Archive			
Trips Count	Distance miles	Duration Hours	Distance miles	Duration minutes	Speed mph	Tables Count	Records Count (BN)	Obj. TB	Video TB
4,973,641	31,684,117	1,127,542	6.5	13.7	28.1	24	87.1	6.9	0.0

Enhanced Driving Database (UMTRI DAS)

Exposure			Per Trip Average			Database and Video Archive			
Trips Count	Distance miles	Duration Hours	Distance miles	Duration minutes	Speed mph	Tables Count	Records Count (BN)	Obj. TB	Video TB
280,574	2,174,179	77,714	7.7	16.5	28.0	25	18.5	0.9	16.4

Figure 33. Safety Pilot Model Deployment Exposure Summary

UMTRI DAS and Associated Sensor Suite

For SPMD a major component of the sensor suite install on all vehicles (except motorcycles) with the UMTRI DAS, is a Mobileye (ME) vision-based ranging sensor. This sensor is a mono-camera based machine vision technology that uses vision recognition algorithms to “interpret” a scene and derive information that is critical in the design and implementation of Advanced Driver Assistance Systems (ADAS). MobilEye is a supplier of this technology for production automotive crash warning products, including GM, Volvo, and BMW.

A requirement in SPMD was to install a forward-facing ranging sensor on all vehicles equipped with the UMTRI DAS. The purpose of this sensor is to provide information about the forward scene such as the number of same and opposing direction vehicles, the relative distance and speed of other vehicles, and relative location of vehicles with reference to the host vehicle. Additionally, an autonomous ranging sensor also adds to the general usefulness of the data archive collected during SPMD by giving researchers a wealth of information about the vehicular environment in front of the host vehicle at all times. These data are used to study the intra-vehicle dynamics between the host vehicle and other vehicles in its path and can be used to derive surrogate measures of traffic density. Combined with the host vehicle state, ranging sensor measures can be used derive longitudinal measures of the lead vehicle such as speed, implied brake status, and longitudinal acceleration. Finally, the MobilEye sensor also tracks lane boundary markers and provides measures of the host-vehicles position with respect to a lane markers. These measures, although not a requirement for DAS equipped vehicles, are very useful and were used to complement and enhance the current analysis. Details are given below.

The fact that the SPMD dataset contains measures derived from a sensor similar to the same measures in the current dataset was the most compelling reason to use this data set over other readily available data sets at UMTRI, like Integrated Vehicle-Based Safety Systems (IVBSS used a radar as its ranging sensor) or road departure crash warning (RDCW).

Lane Departures and Lane Changes

The first steps toward leveraging the SPMD data in the analysis of the current data in terms of LDW was to define and identify similar lateral events in the SPMD. To do this analysis there were two main tasks:

a) Identifying lane departure events—the start of which is defined as the lateral offset distance (the distance between the ME camera and the boundary) indicates that a wheel has touched or crossed the boundary but the vehicle centerline never crosses the same boundary (i.e., the lateral distance between the ME camera and the adjacent lane boundary has not reached zero). The end of lane departure events is defined as the offset distance indicating the same wheel has return to the original lane.
b) Identifying lane change events—similar to lane departure events only now the lateral distance does indicate that the vehicle centerline has crossed the boundary. For an example and illustration of the lane change, see the section below on the lane change algorithm. A summary of the lane-changes from SPMD is given below.

Lane Departure Events

The procedure to find lane departure events in the SPMD data uses lane-offset distance and lane-offset confidence measures reported by the ME sensor. Lane-offset distance is ME estimate of the distance between the lane boundary and the ME camera/center of the vehicle (if the camera is offset from the lateral centerline of the vehicle a correction is applied by the sensor to the offset). Lane-offset distance is measured for lane boundaries to the right and left of the vehicle. Similarly, lane-offset confidence is calculated for both the left and right offset distance measures. All lane departures have direction either to the left or right (with respect to the driver orientation). A lane departure to the left starts when the left front wheel (closest to the camera) reaches or crosses the boundary on the left and ends when that same wheel returns to inside of the original lane. The corresponding definition is the same for a right departure. For all lane departures from SPMD the lane-offset confidence in the direction of the departure is “high.” For each lane departure the following measures are captured.

1. The direction of the departure (1=left; 2 = right)
2. The start and end time of the departure (hence its duration)
3. The maximum distance of the departure relative to the front wheel. For example, for a left departure, a distance of 0.2 m indicates that the left wheel crossed the boundary on the left and then travelled laterally an additional 0.2 m before the distance decreased and the wheel returned to inside the original lane boundary.
4. The boundary type that was crossed (Dashed, Solid, Double, etc.)

Table 27 shows the distribution of lane-departure event counts from SPMD for passenger cars as a function of lane boundary type. A total of 613,859 lane departure events where used in the analysis of the current data. Also shown in the table is the average maximum distance of a lane departure as function of boundary type.

Table 27 Safety Pilot Lane-departure Summary

	Count		Max. Distance, m	
	Left	Right	Left	Right
Dashed	31,330	56,640	0.19	0.20
Solid	154,164	248,404	0.16	0.22
Undecided	1,283	3,294	0.25	0.27
Double	113,712	4,904	0.21	0.19
Botts Dots	59	69	0.20	0.20
All	300,548	313,311	0.18	0.21

Lane-change Events

Appling the lane-change algorithm (explained below) to passenger cars in the SPMD dataset, a total of 378,187 lane changes were identified. Table 28 shows how these lane-changes are distributed left and right and as a function of the boundary type crossed. The table also gives average estimates of the lateral rate of lane-changes. Here lateral rate is defined as an average vehicle track width (1.8 m) divided by the amount of time it takes for both front wheels to cross the lane boundary.

Table 28 Safety Pilot Lane-change Summary

	Count		Lateral Rate, m/s	
	Left	Right	Left	Right
Dashed	123,555	162,087	0.68	0.68
Solid	29,555	20,674	0.61	0.64
Undecided	5,720	2,578	0.42	0.50
Double	30,947	2,815	0.62	0.53
Botts Dots	126	130	0.70	0.70
All	189,903	188,284	0.65	0.67

Lane-change Algorithm

To identify, and operationally define lane-changes for use in the current dataset, in the SPMD, the following algorithm was developed. Consider Figure 34, which shows time-series data of the four measures used in the algorithm. Two of the measures are offset distances, which is the estimated distance from the boundary to the sensor (camera in this case) to the left and right. The other two measures are an estimate of the quality of this distance estimate. For this algorithm, the quality measures should be high (value of 2 or 3) for both the left and right offset distance at the time of the lane change. In the example, the left quality measure is a value of 3, while the right starts at a value of 2 and then changes to 3 when the lane change occurs as shown in the center plot of the figure.

Given high quality, the algorithm is based on a large change in the offset estimate for both the right and left offset measures which occurs when the sensor crosses over the lane-boundary line and the system switches to monitoring the new lane boundary markers on the left and right. In the example, which is a lane-change to the right, consider the upper plot. It shows the right offset distance approaching 0 m at around 4 seconds, while the left offset distance approaches -3.6 m (or the width of the lane), then at the time of the crossing (4.1 s), the offset values transition (large step function) to monitoring the boundary lines in the new lane, meaning the right offset values becomes 3.6 m while the left offset value is 0 m. To identify the lane-change event the algorithm simply takes the difference between the current right and left lane offset value and the corresponding previous offset value and if the absolute value of this difference is greater than a tolerance value of 2 m the event is flagged as a lane-change. This comparison of the current and previous offset values (for right and left, respectively) is illustrated in the bottom plot of the figure. The direction of the lane change is determined by the sign of the difference calculation. A negative value for the difference in both right and left offset is a lane-change to the right, a positive value is a lane-change to the left.

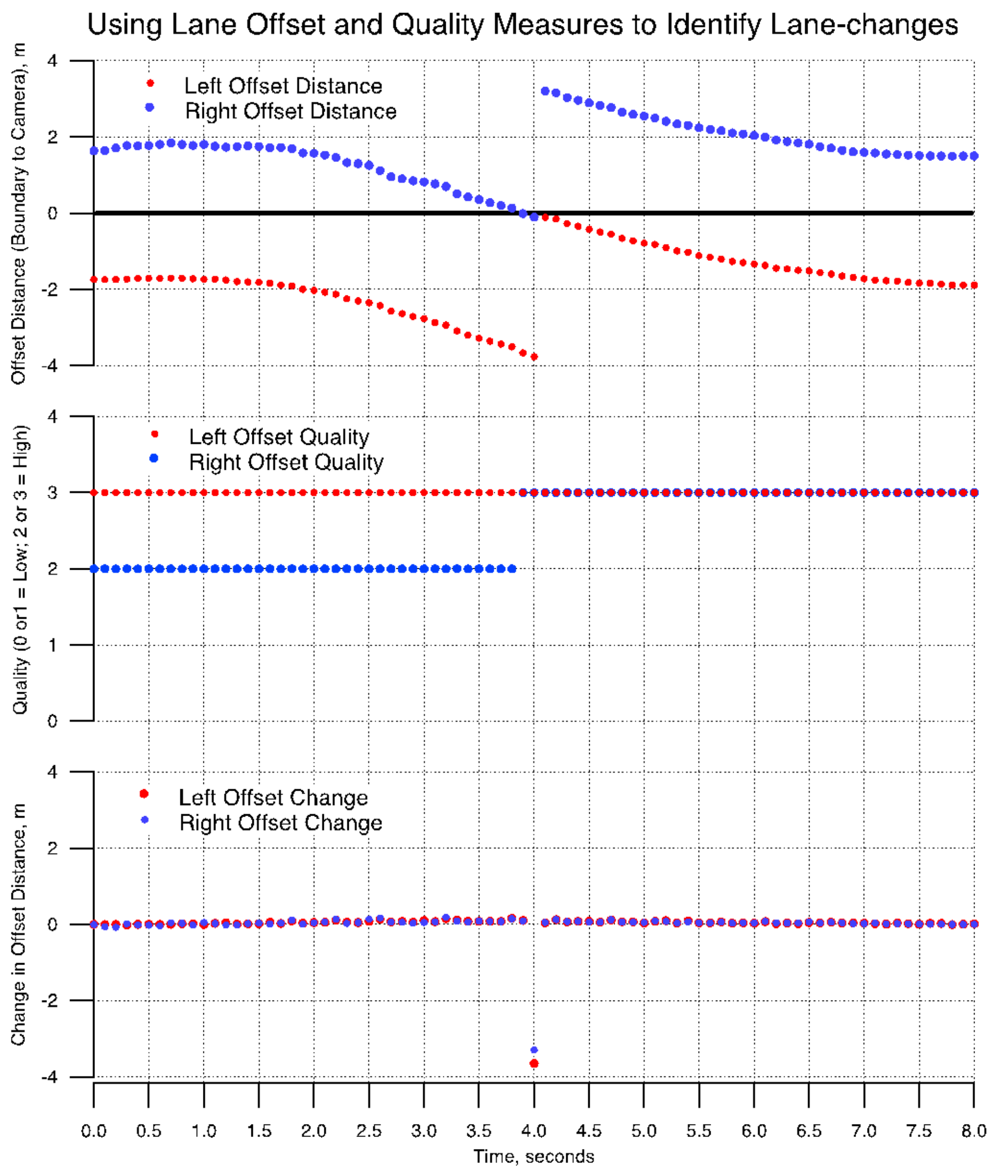

Figure 34. Identifying Lane-Changes with Offset and Quality Measures from Safety Pilot FOT

Forward Conflict Events

The SPMD dataset includes FCA events but they are based on the longitudinal conflict measures derived from the wireless V2V messages exchanged between the host (following) and lead vehicle. To develop FCA events that are similar to those from the current dataset the MobilEye ranging sensor data had to processed to derive common metrics that are often associated with assessing longitudinal conflicts found in rear-end type crash scenarios. These were derived for the closest-in-path-vehicle (CIPV) and the metrics include:

- Lead vehicle (LV) Speed (defined as host speed + range-rate),
- LV Longitudinal Acceleration (LVAx: time derivative of LV speed),
- Time-Gap or Headway (Th: Range / Host Speed),
- Simple Time-to-collision (TTC: -Range-rate/Range), and
- Required deceleration (DecelAvoid: constant level of deceleration needed for the host vehicle to avoid a collision assuming current kinematics continue).

The algorithm used to identify pseudo-FCA imminent alert events in the SPMD data using these conflict metrics used the following definitions for three cases. For a stopped lead vehicle, the following must all hold the following.

- HV Speed > 11. 2 m/s
- CIPV = 1
- LV Speed between -1.0 and 1.0 m/s
- Range < 65 m
- TTC < 3.5 s
- Criteria persistence of 0.3 or more consecutive seconds

For a close lead vehicle, all the following conditions must hold.

- HV Speed > 11. 2 m/s
- CIPV = 1
- LV Speed > 1.0 m/s
- Range < 10 m
- DecelAvoid < -0.5 m/s2
- TTC < 14 s
- Criteria persistence of 0.5 or more consecutive seconds

If neither the stopped or the close lead vehicle cases hold, the conditions for which a psuedo FCA event is defined in the general case is that all of the following hold.

- HV Speed > 11. 2 m/s
- CIPV = 1
- LV Speed > 1.0 m/s
- Range < 65 m
- DecelAvoid < -3.0 m/s2
- TTC < 14 s
- Criteria persistence of 0.5 or more consecutive seconds

The results of this processing identified 26,413 FCA events in the SPMD dataset. These events were subsequently used to populate a table with similar measures to the current dataset using the same time window surrounding the events. Next, conditional algorithms were developed on this subset of the SPMD data. These algorithms were then modified by reviewing the SPMD video around the FCA in order to classify and group them into different scenarios. These same conditional algorithms were then applied to the current dataset to form and operationally define the scenario categories that look at the host-vehicle response in terms of lead vehicle persistence and host vehicle longitudinal and lateral response to the forward conflict.

OnStar FCA Scenario Classification

A significant portion of the current data analysis was undertaken to classify the FCA into a set of scenarios for analysis purposes. Previous work, by UMTRI, GM, and other organizations has been undertaken to categorize the complex interactions that can occur between a host and lead vehicle in FCA-relevant longitudinal conflicts that might result in a crash. Two major inter-related areas of conflict research are algorithm/metric development and scenario classification.

Algorithm development implies deriving meaningful measures that represent the level of conflict and crash threat urgency between vehicles, especially as conceived by the driver. In many cases, the measures need to match the same level of immediacy that a vigilant driver would feel if they experience the same driving situation. In other cases, these measures need to reflect high conflict situations when even an attentive driver may not perceive the immediate sense of conflict. For example, in high-speed situations, if there is considerable range between two vehicles and the lead vehicle does an unlikely, aggressive braking maneuver, the driver of the following vehicle may not perceive the immediacy of the conflict due to the longer distance between the vehicles. This is not the case with accurate ranging sensors that can "see" and measure relative speed, and use that information prompt the driver attention to a higher level of awareness.

Scenario classification involves grouping similar conflict events in order to decide which measure best represents the complexities of the conflict. In short, scenario classification, is the conditional statements in an FCA decision tree that decides which rules are going to work best to estimate the classification of a a current situation. In this research, using the current dataset, scenario classification and conflict metric derivation were undertaken to attempt to more fully understand how a production FCA system performs under a wide range of naturalistic driving situations across a wide geographic span. The categories and general rules of FCA imminent alert scenario classification, based on information reported by the forward-looking camera sensor, included:

- Same, new or no lead Vehicle — In cases where the post-event range value was reported to be zero, this indicated that no LV was reported by the forward-looking sensor at the 4-sec post-alert event time. To determine if the same LV was reported to be persistent at the post-event time each of the following three rules had to be satisfied (<u>if any of these rules fail, the LV was considered "new"</u>):
    1. If an estimated final range (based on the range at the time of the event and an average range-rate—measured at event and 4 s later) was within 5 meters of the actual final range, and
    2. If the estimated acceleration of the LV between event and post-event was within acceptable thresholds
    3. If the final LV speed was between -1 and 40 m/s, than the LV was considered persistent
- In the case with the same LV after 4 seconds:

- Host vehicle (HV) responding to a slowing LV—if the estimated average acceleration of the LV was less than -0.55 m/s^2, then the LV was considered slowing. The threshold value was derived from an analysis of the distribution of average host vehicle acceleration values where an inflection point was found at this threshold. This value is intended to represent the difference between a coasting event without foundation brakes and a slowing event with the foundation brakes. The host vehicle deceleration distribution is shown in Table 33.
  - Host vehicle responding to a stopped LV—If the speed of the LV was estimated to be between -1.5 and 1.5 m/s the LV was considered stopped.
  - Host vehicle responding to a constant speed or accelerating LV—all other cases, the LV was considered constant speed or accelerating.
- In the case where there was estimated to be a new or no LV after 4 seconds the following rules were used to classify scenarios:
  - Oncoming LV —if the estimated derived speed of the LV was determined to be less than -1.5 m/s, then the LV was considered oncoming (in oncoming situations, range-rate is less than zero and its absolute value is greater than the host vehicle speed).
  - Host vehicle performs a lane change—lane changes by the HV were estimated by analyzing the lane change and lane departure results from the Safety Pilot Model Deployment FOT. The derivation of these events was covered earlier in this section. By structuring the SPMD data similar to the current data, and looking at the difference in lane-offset between event and post-event, the two distributions shown in Figure 34 were derived. This figure shows the absolute difference between lane offset at alert even and post-alert event lane offset along the x-axis. The solid lines represent the fraction of data points in each distribution (the left y-axis), while the dashed lines are the cumulative fraction of data points (right y-axis). This figure shows a clear distinction between the lane change (shown in red) and the lane departure distribution (shown in blue). For estimated offset change values between 0 and 0.5 m there is a 90 percent chance of a lane departure, while for values more than 0.5 m there is 95 percent chance of a lane change. A similar analysis was done with the SPMD FCA events, and although the two distributions are not as distinct, they do follow the same pattern and have a similar crossing values of 0.5 m. Also, note that although the figure only shows left offset values, using right lane offset values was also found to give the same distributions. Based on these distributions, the HV was flagged (or operationally defined) as making a lane change if the estimated change in lane-offset (right or left) was more than 0.5 m.
  - Host vehicle does not perform a lane change or is unknown
    1. LV Turns or makes a lane change—in cases where the HV data indicates detected lane boundary markers at event and post-event and it is shown that the Lane-offset is estimated to be less than 0.5 m, it is assumed that the HV does not change lanes, and since the LV does not have persistence, it is assumed that the longitudinal conflict is resolved by the LV either clearing the HV path by turning, making a lane-change, or following a path that is orthogonal to the HV path.

2. Unknown—this category captures the remaining FCA imminent alert events that do not fall into the ones described above. In these events, the lane offset measures are unreliable either due to low reported confidence or estimated values that are not typical of normal lane geometry, i.e., values not between 0 and 3.6 m.

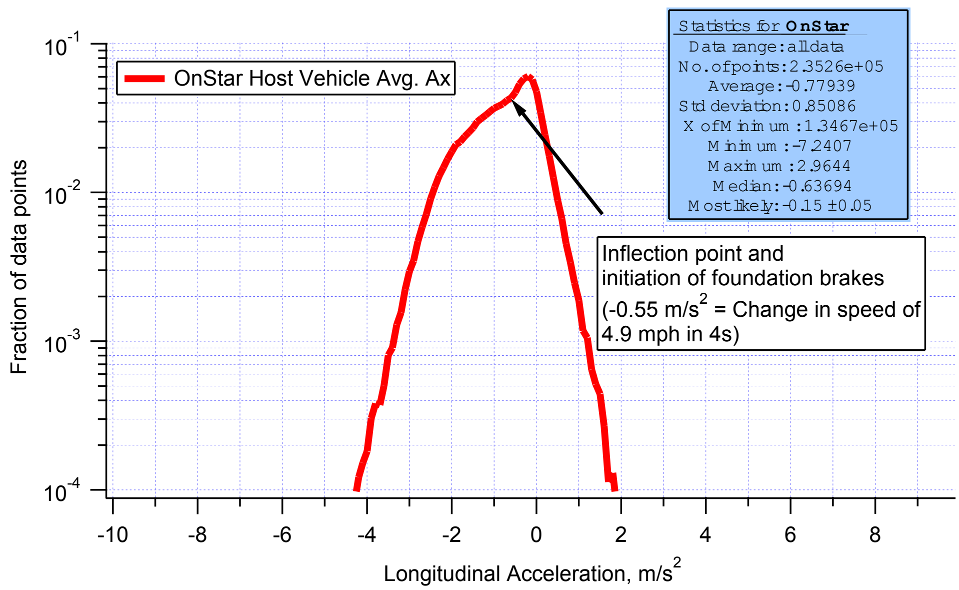

Figure 35. Distribution of average host vehicle acceleration between the FCA and post-event times.

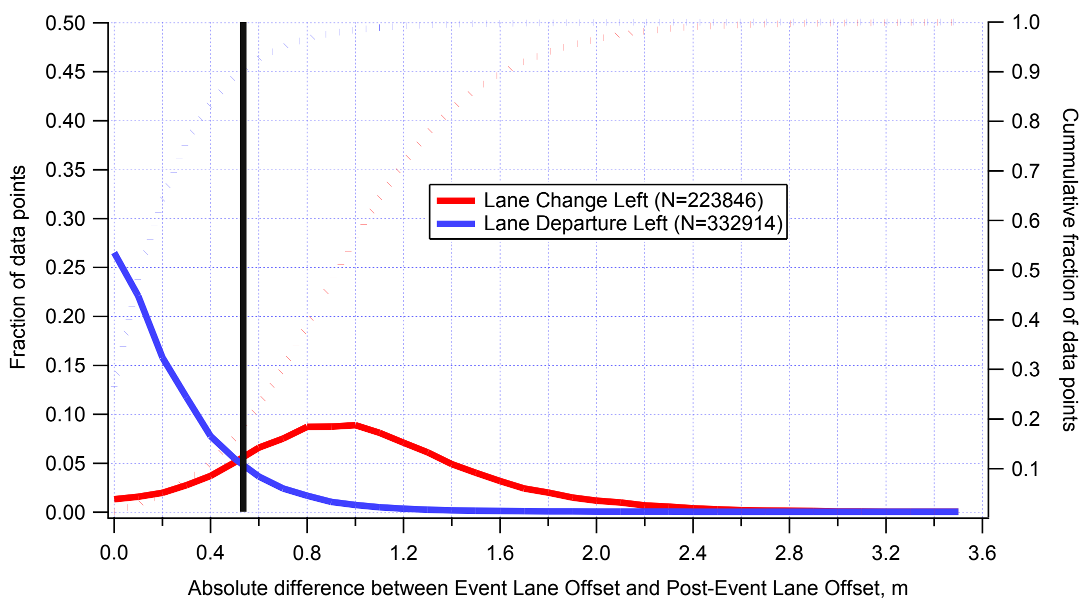

Figure 36. Left lane-offset change for lane change and departure events from Safety Pilot

Appendix C Data Analysis Details

Research questions are numbered according to the data analysis plan written at the beginning of the project. In some cases, questions have been combined into a single analysis.

SQ1: What is the distribution of system availability (rate per time), and how does it vary by speed?

Method: Availability rates were calculated per unit of time, as aggregated within vehicle (across trips). These rates include only driving at speeds above the set threshold for each system. A histogram of overall rates were constructed. In addition, the general reason for any unavailability were tabulated. All of these measures represent descriptive statistics on the sample.

Constraints (filtering): For LDW, only samples at speeds greater than 35 mph were used. For FCA, only samples at speeds greater than 25 mph with a target present were used.

Results: First, the availability (ready-to-assist or RTA) rates are explained. Since the systems are always unavailable under the set speed thresholds, the analysis of the availability rate was conducted for the speed ranges greater than the threshold in which the safety benefits could be anticipated. Moreover, FCA is available only when a target is detected ahead in the same lane as the host vehicle (i.e., closest in path vehicle or CIPV).

Figure 37 and Figure 38 show histograms of the average RTA rates per vehicle for LDW and FCA, respectively, for each vehicle model. Their characteristics are very similar regardless of vehicle model. The median rates are about 80 percent for LDW and 90 percent for FCA; SRX shows a slightly higher availability rate compared to the other models in both systems. The long-tailed distributions to the left indicate that some vehicles were rarely travelling below the minimum operating speed of the LDW or FCA system and the average system availability rate is significantly vehicle-dependent.

Note: The RTA data are stored in single valued counters, and a classification by speed bins is not available. However, since RTA does not occur at speed under the threshold, simply using the speed range above the threshold for the denominator of the fraction gives the rate of RTA above that threshold. (As mentioned above, the CIPV condition is also required, so the speed counters for the case in which a CIPV exists are used.)

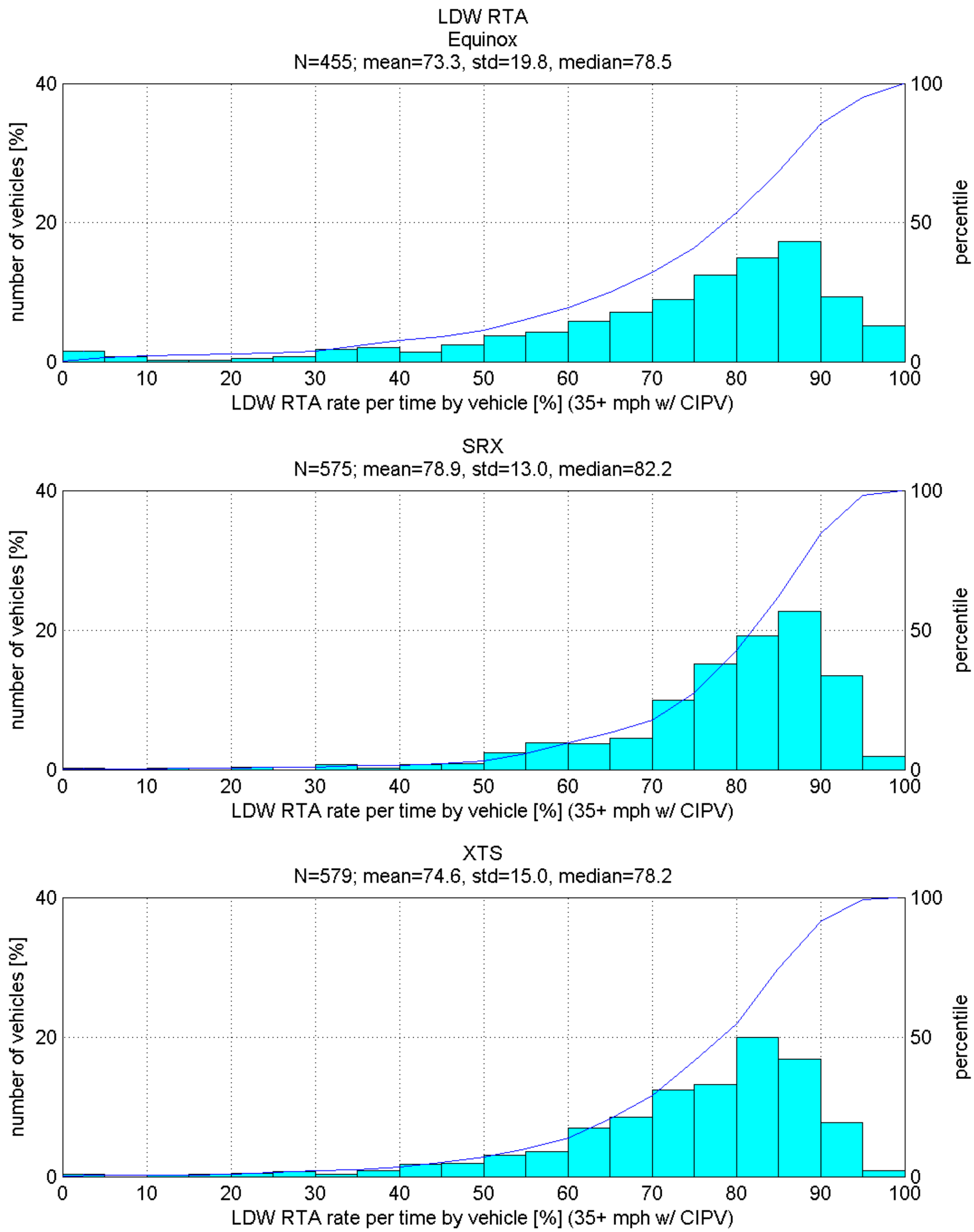

Figure 37. Availability rate of LDW

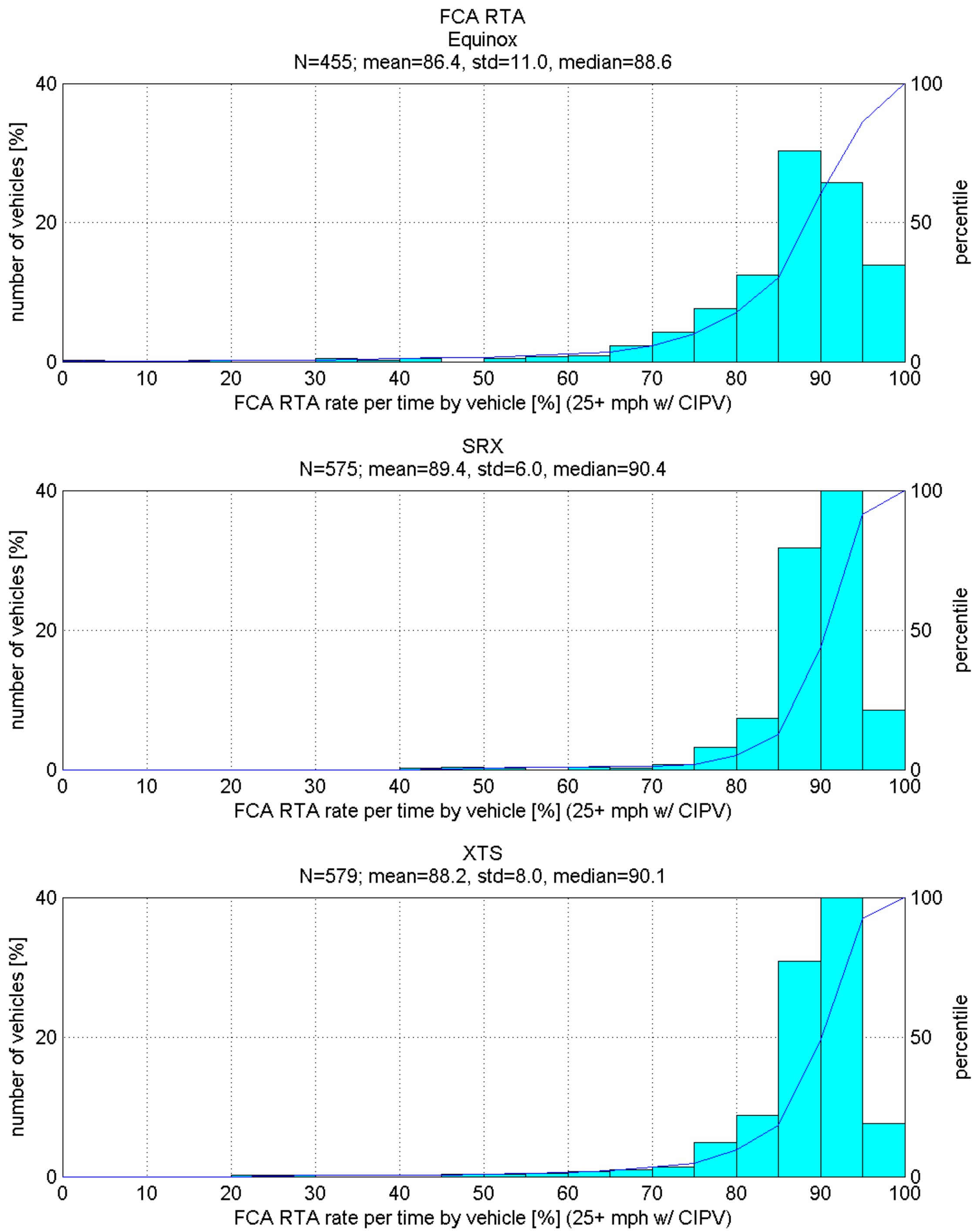

Figure 38. Availability rate of FCA

Next, the unavailability (NRTA) rates are investigated. For each of LDW and FCA, there is a set of reasons which cause NRTA - Table 29 summarizes it along with the associated bitmap indices (see Appendix A). There are six reasons for LDW NRTA and five for FCA NRTA including an additional reason that is not assigned a bitmap index, “a closest-in-path vehicle not detected.” If NRTA occurs for multiple reasons at the same time, both reasons are recorded in the respective counters, and therefore the sum of those counters for all the unavailability reasons can be greater than the total driving time.

Table 29 Reasons for the system unavailability

Bit	LDW	FCA
0	Speed under threshold (35 mph)	Speed under threshold (25 mph)
1	Adverse weather	Adverse weather
2	Low visibility	Low visibility
3	Invalid left lane position	Speed above threshold (25 mph)
4	Invalid right lane position	
5	Single lane performance	
		Closest-in-path vehicle not detected

Figure 39 to Figure 44 show the histograms of LDW NRTA rate, and Figure 45 to Figure 47 those of FCA NRTA rate. As a general remark, the FCA NRTA data contain erroneous values as can be seen from unreasonably small rates even for the Bit 0 reason (Figure 39) which should have given ideally a 100 percent of unavailability rate in the speed range between 0 and 25 mph. On the other hand, the shape of each FCA histogram or the relative proportions across different speed bins within the same histogram is reasonable; the shapes for Bit 0, 1, and 2 are comparable to the LDW counterparts and there is no data for Bit 3, which is reasonable. In addition, the occasional inconsistent peaks such as the ones in Figure 46 are due to a small number of samples.

Two comments regarding the LDW NRTA histograms are made here: (1) for Bit 0 the NRTA rate for the speed range, [25, 45) mph is approximately 50 percent because the speed threshold (35 mph) is located at the midpoint of the range; and (2) for Bit 3 and 4, the rates becomes smaller as the speed becomes higher, which implies that different road types are involved in the different speed ranges, e.g., residential area for the first speed bin, the next two or three bins for other surface road, and the higher speed bins for highways.

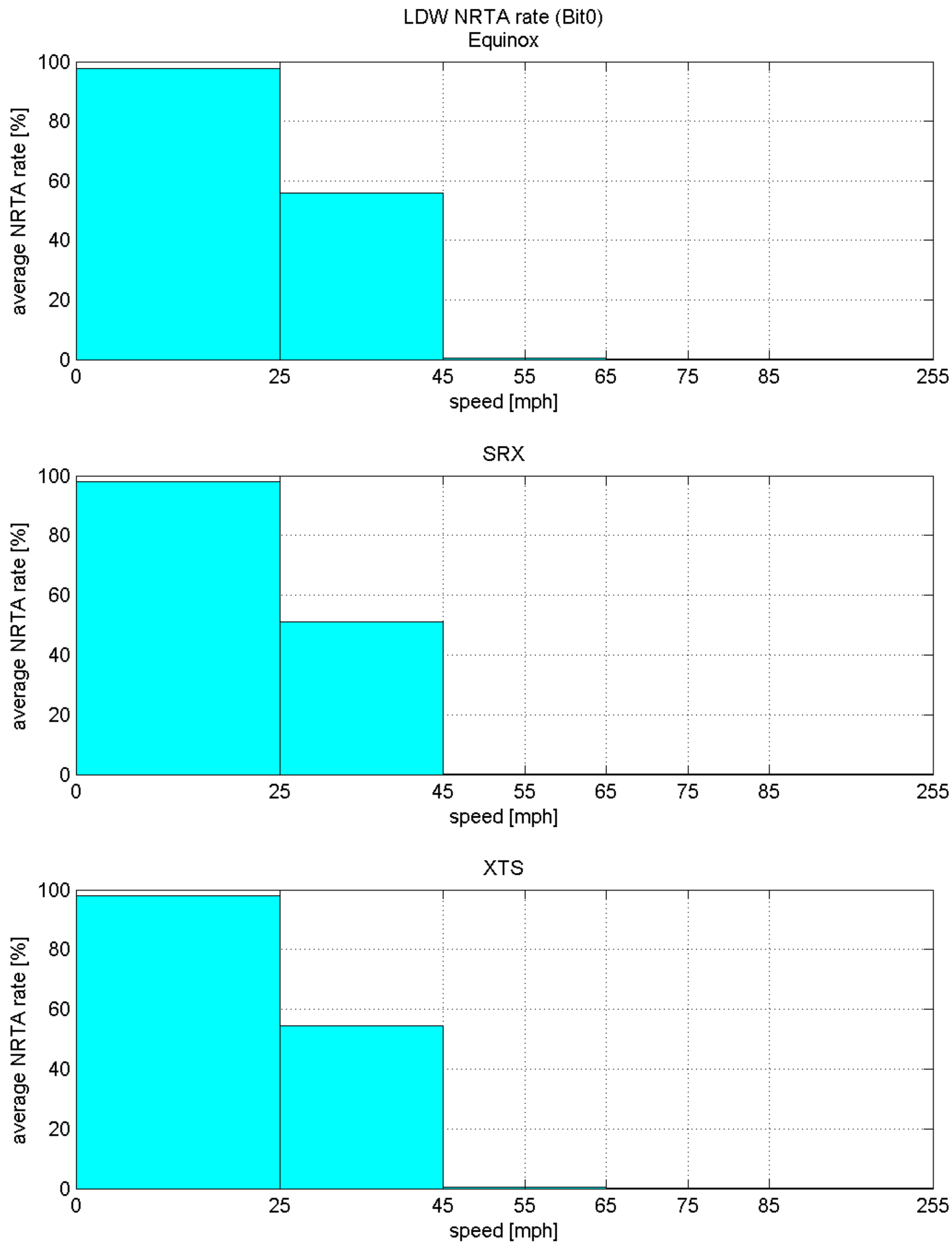

Figure 39. Unavailability rate of LDW (Bit 0: Speed under threshold)

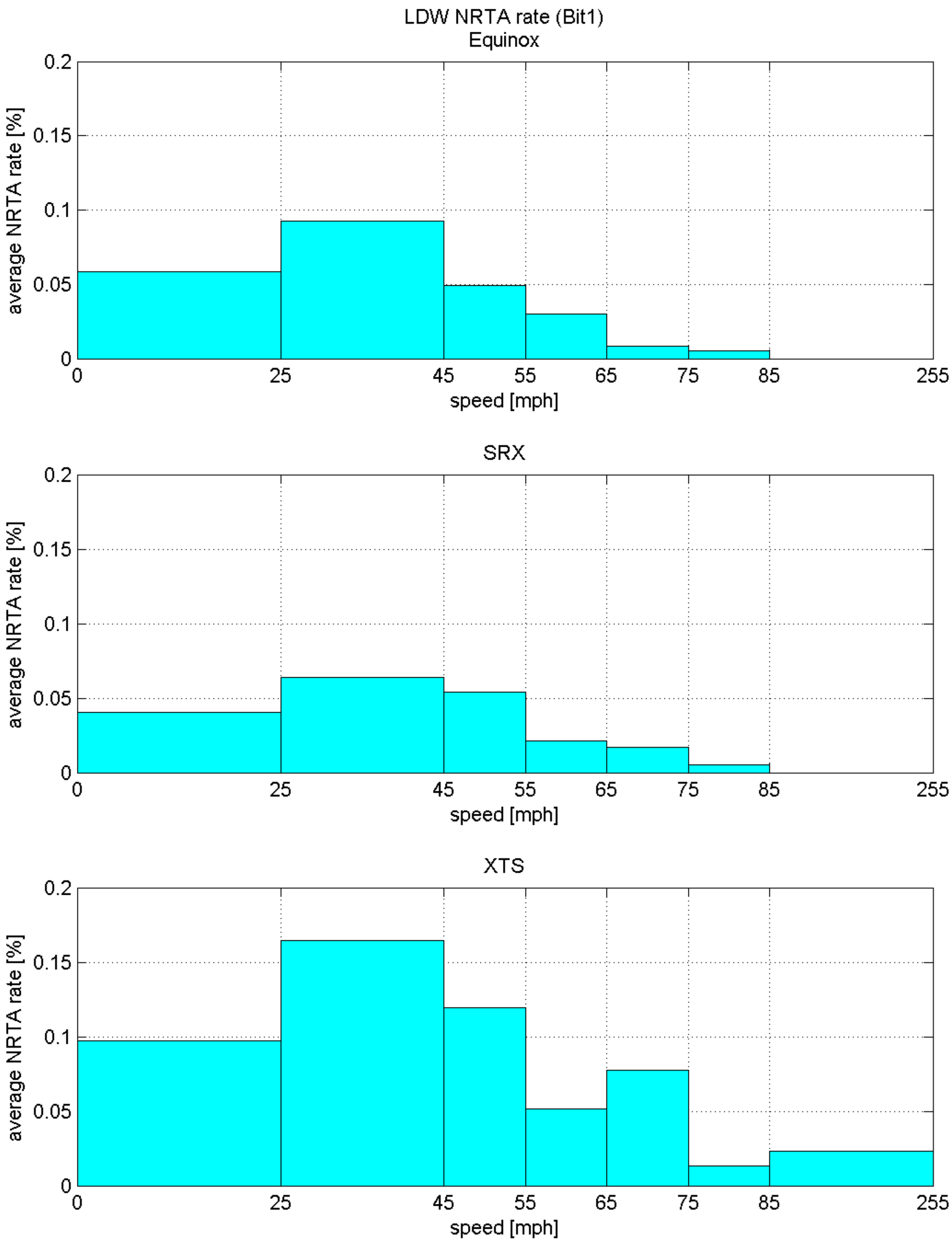

Figure 40. Unavailability rate of LDW (Bit 1: Adverse weather)

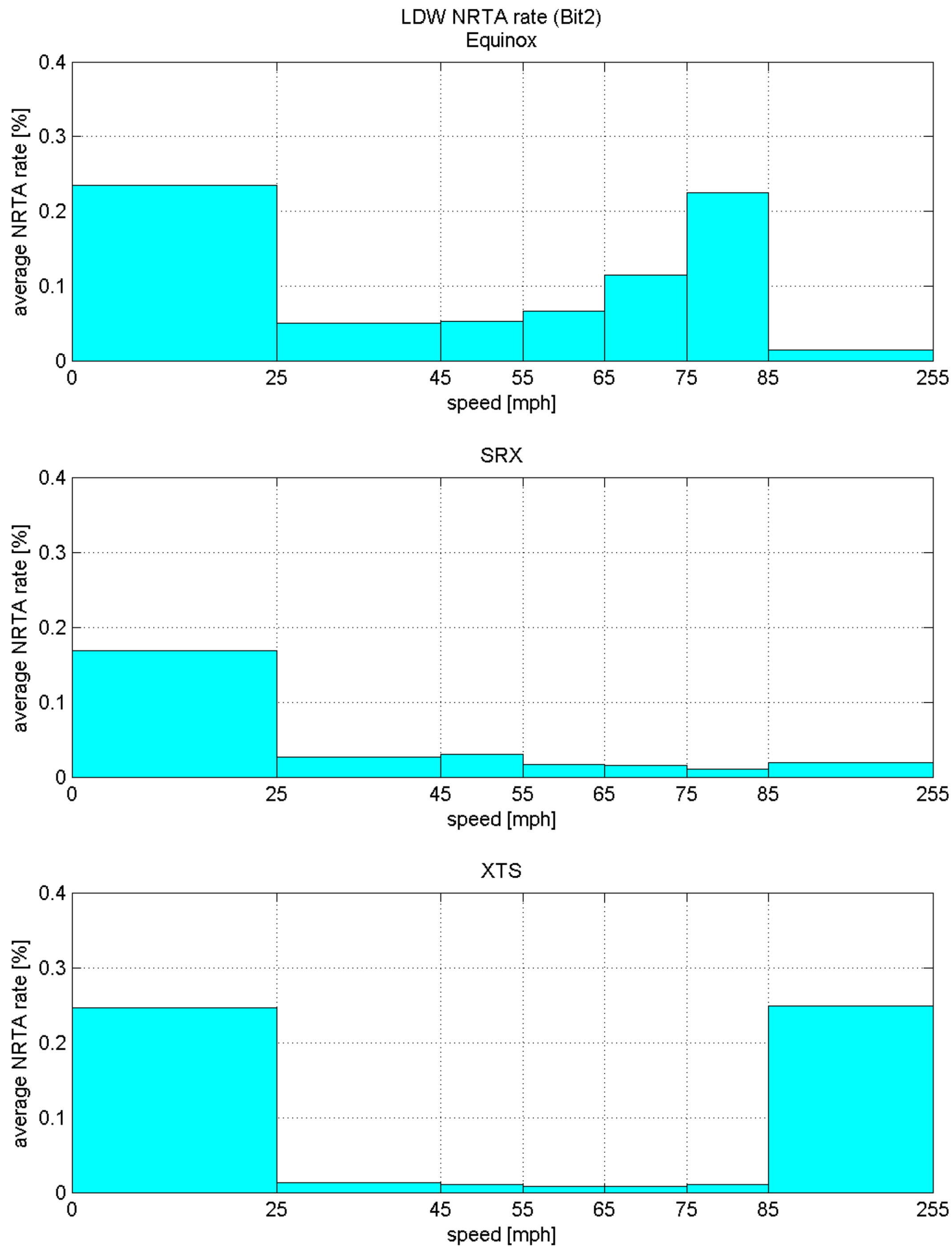

Figure 41. Unavailability rate of LDW (Bit 2: Low visibility)

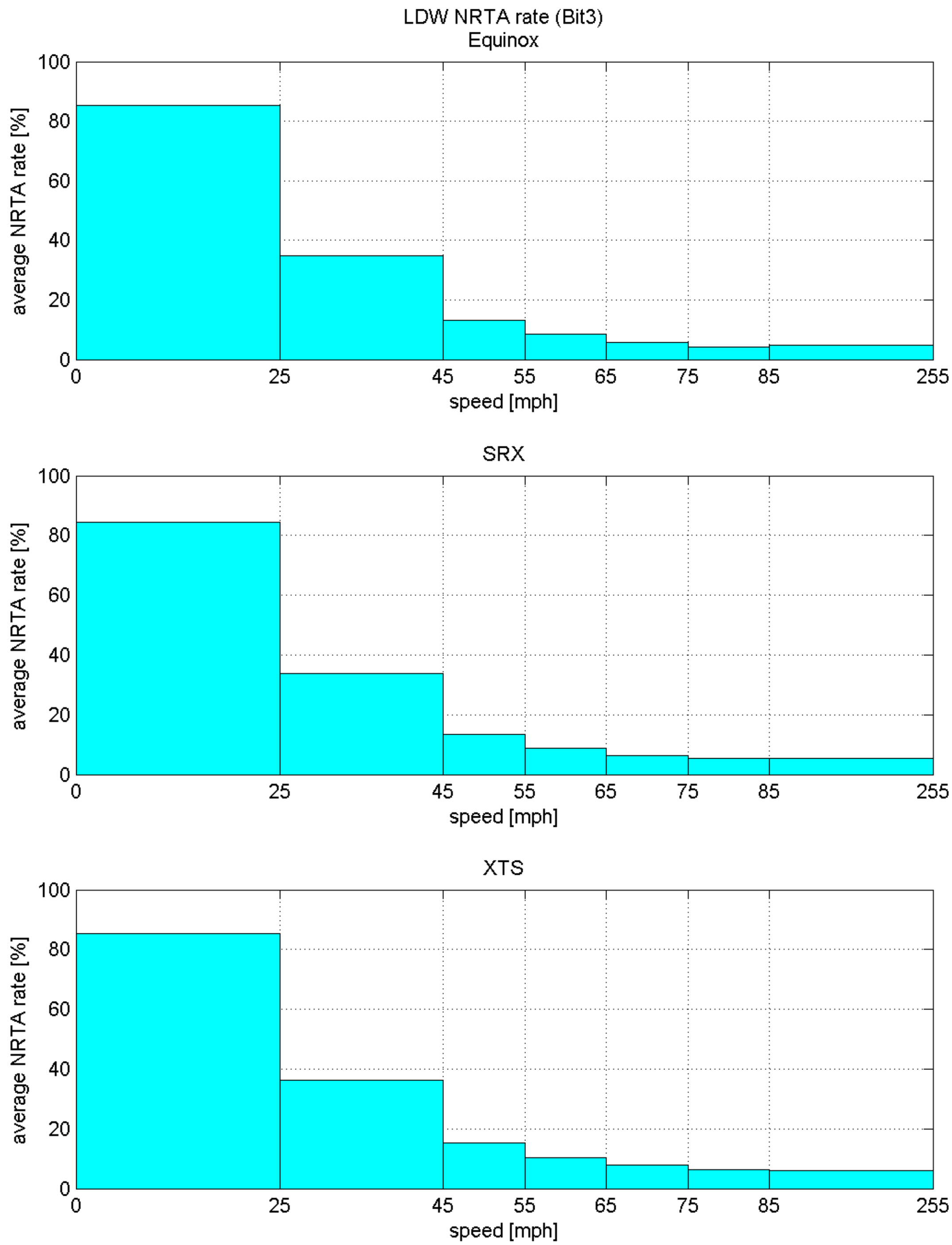

Figure 42. Unavailability rate of LDW (Bit 3: Invalid left lane position)

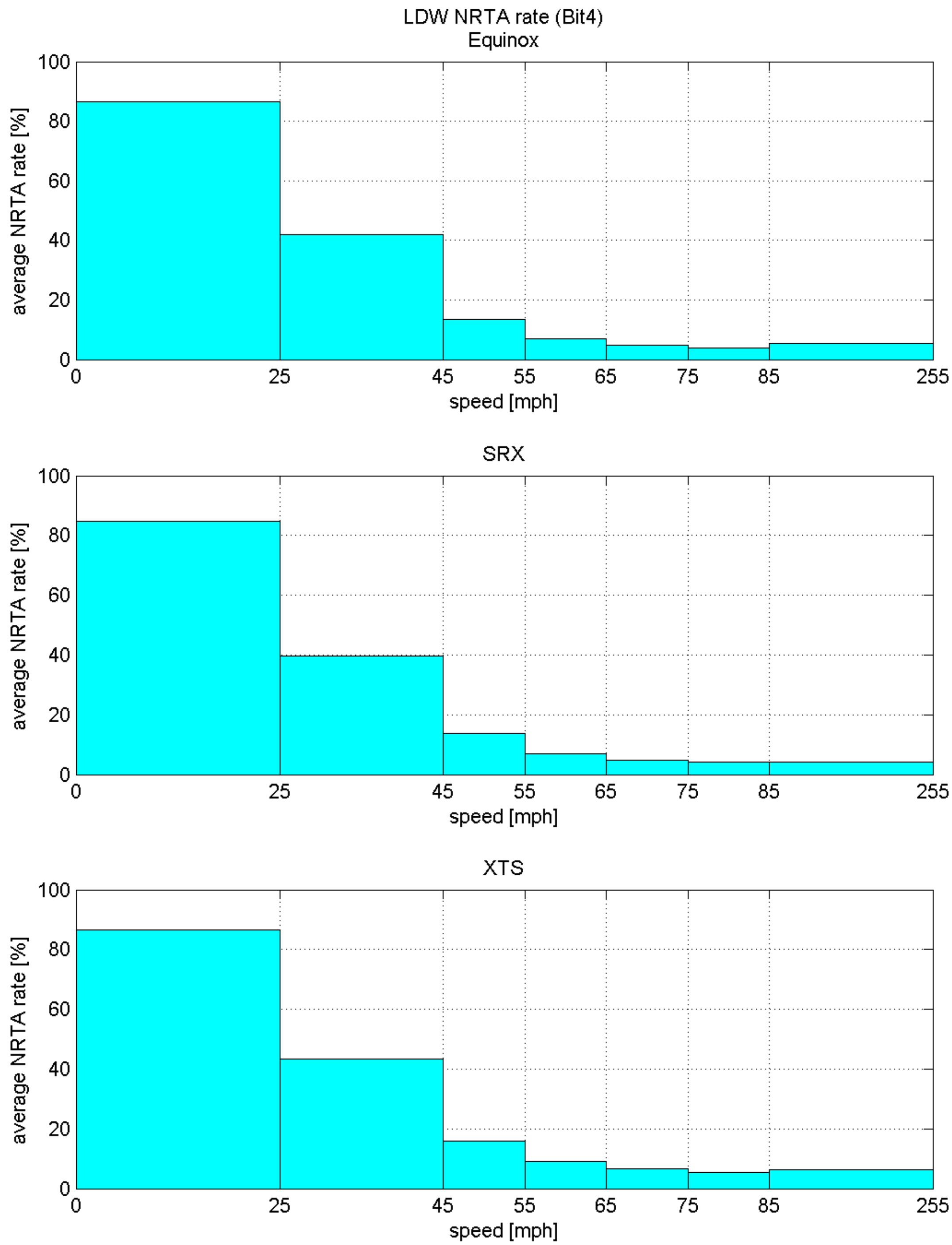

Figure 43. Unavailability rate of LDW (Bit 4: Invalid right lane position)

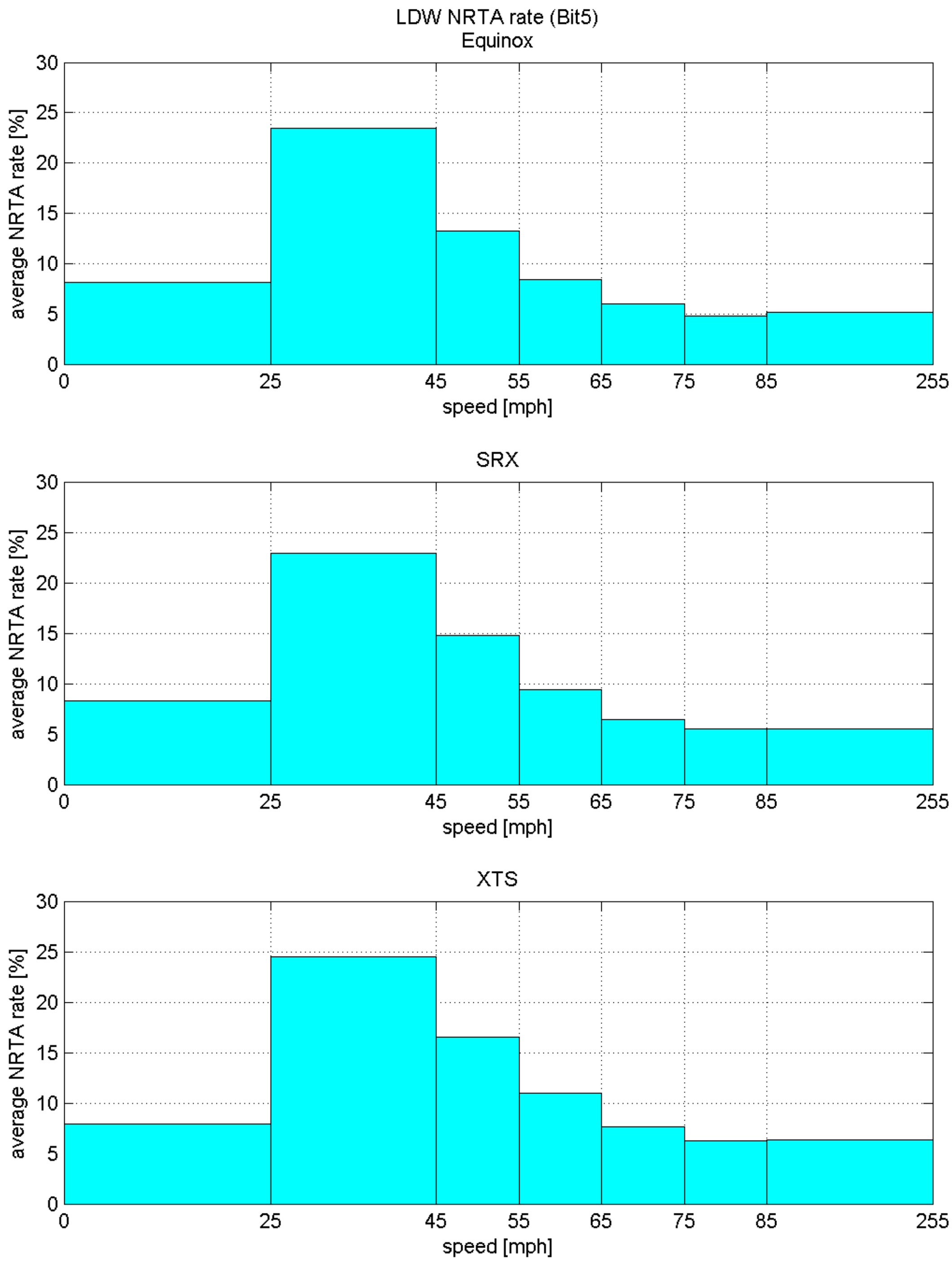

Figure 44. Unavailability rate of LDW (Bit 5: Single lane performance)

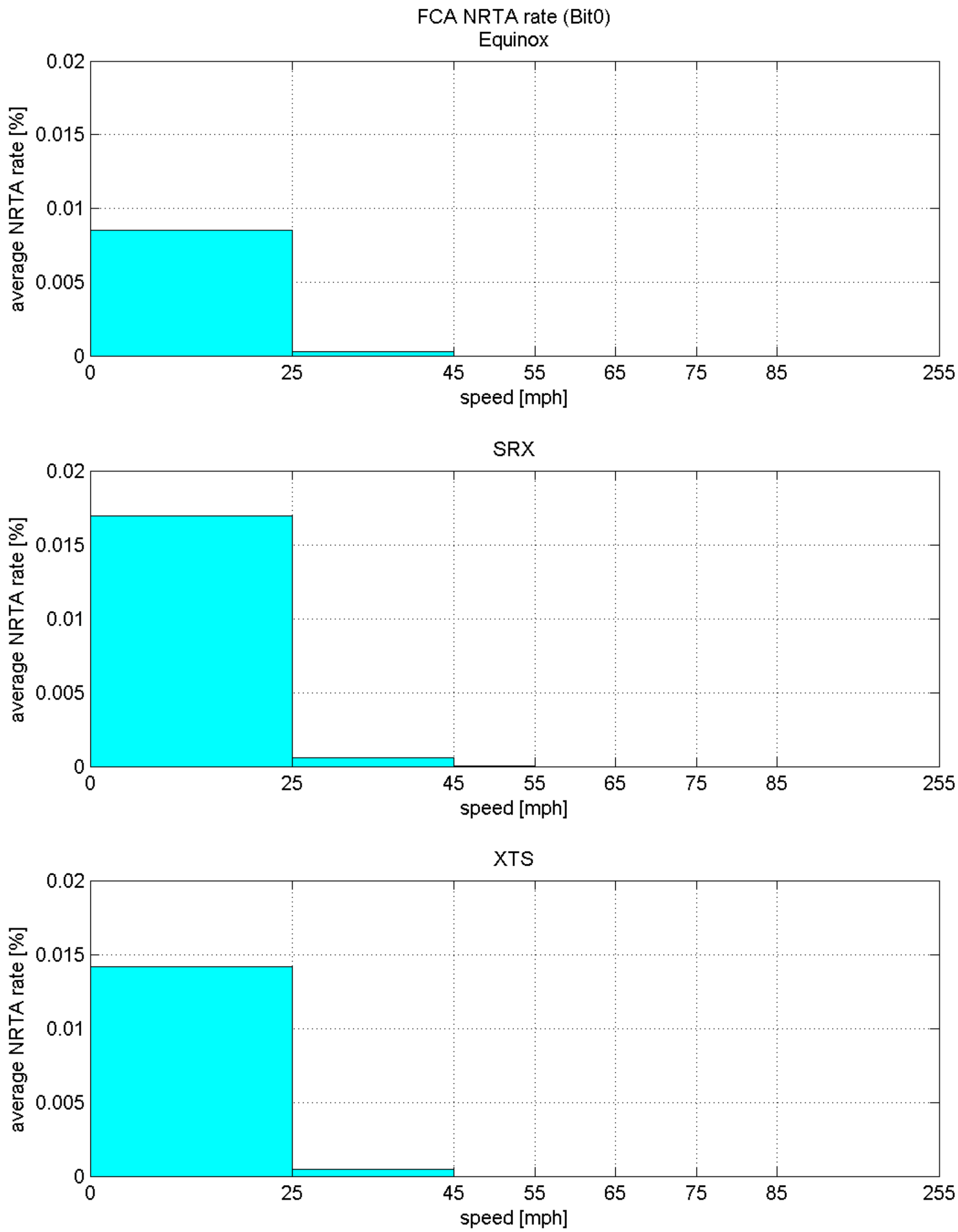

Figure 45. Unavailability rate of FCA (Bit 0: Speed under threshold)

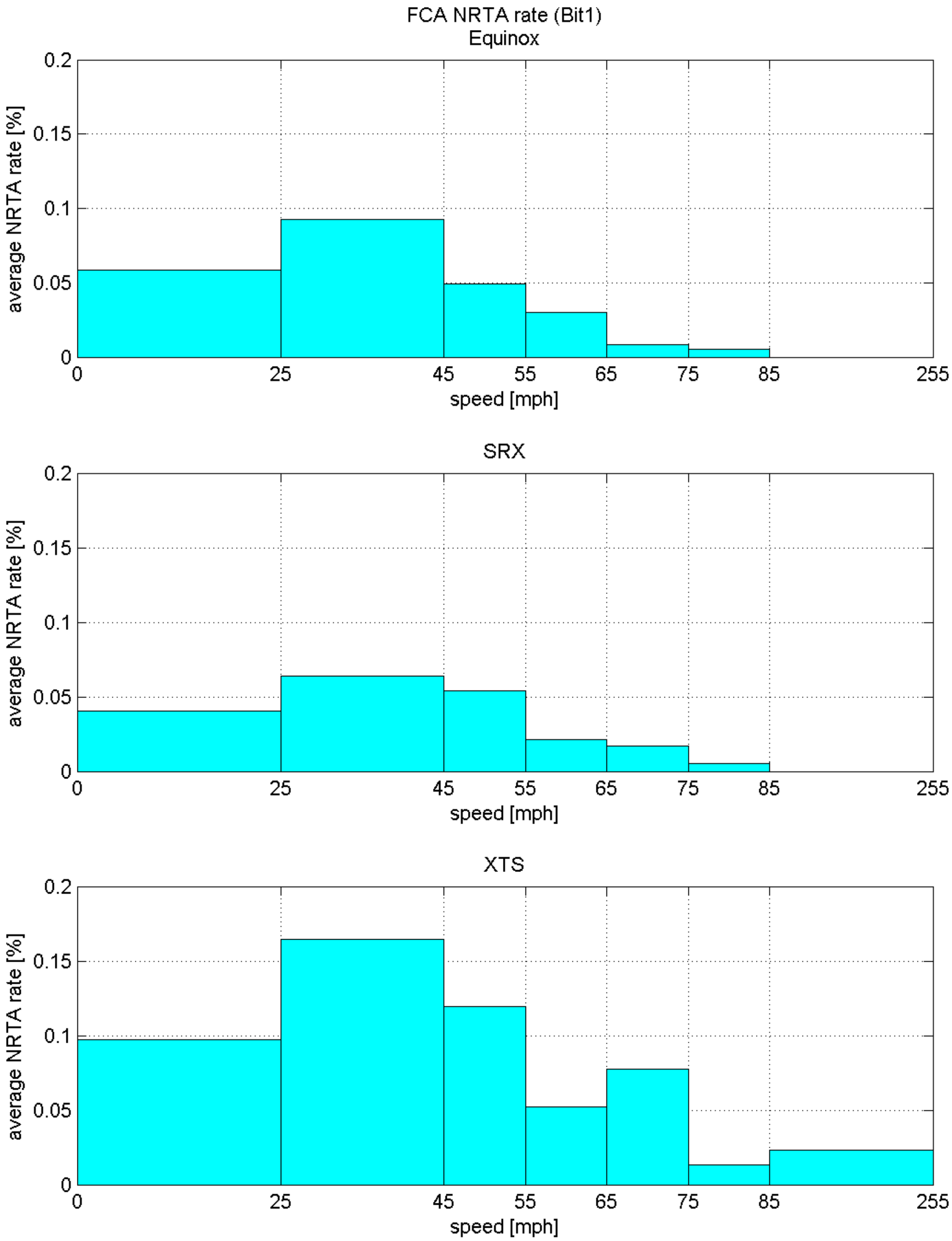

Figure 46. Unavailability rate of FCA (Bit 1: Adverse weather)

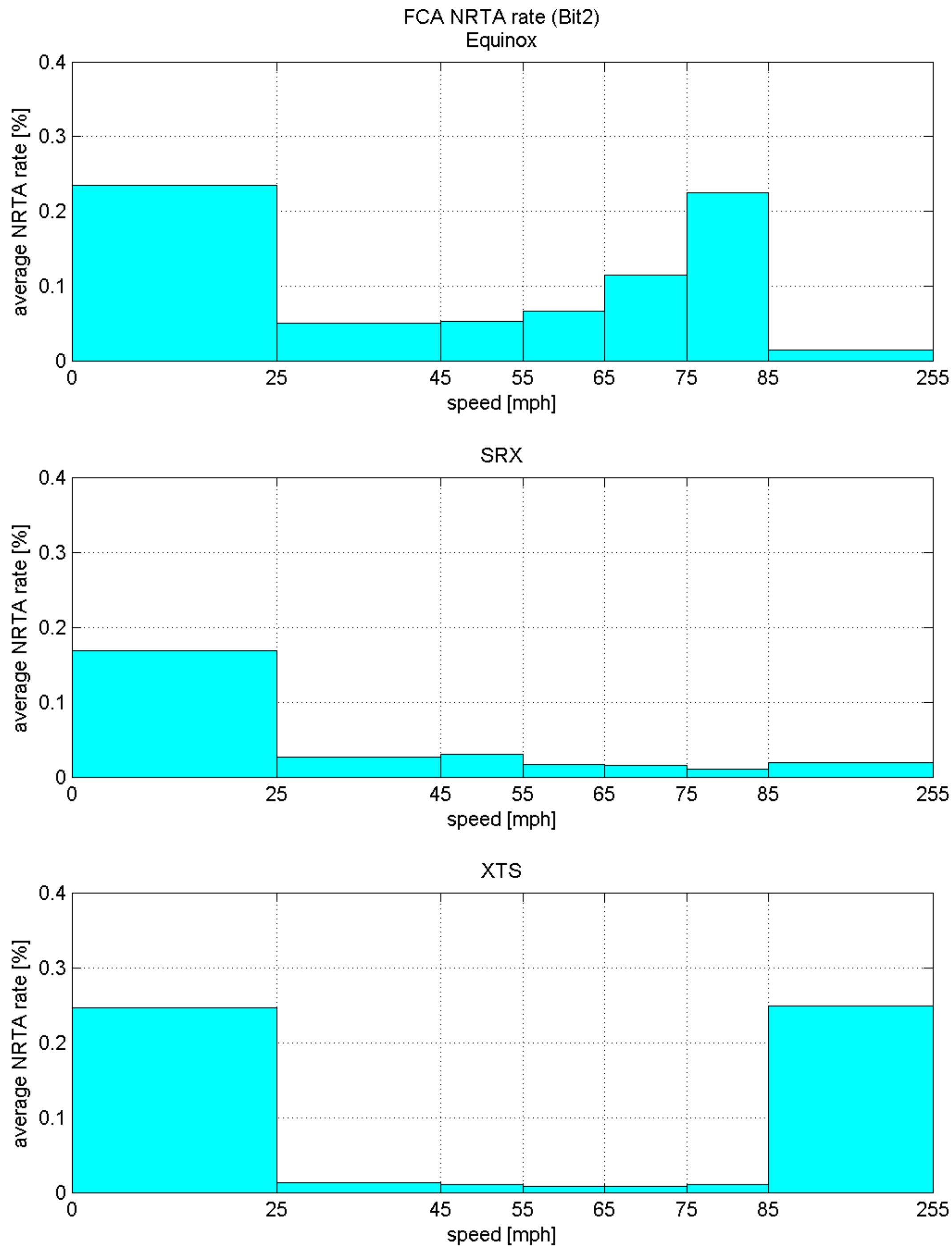

Figure 47. Unavailability rate of FCA (Bit 2: Low visibility)

BQ1/AQ2: (BQ1) How does the system setting vary by time of day, month of study, and vehicle mileage? (AQ2) How do system settings change over time within-vehicle?

Method*:* The focus of this analysis is driver selection of FCA or LDW setting as a function of time and trip characteristics. Each trip was classified by the majority setting on the trip, evaluated using the appropriate system counters, and the models were based on an underlying multinomial (FCA) or logistic (LDW) distributions. Other predictors were limited to those measures that are available at the trip level.

The model form for FCA (multinomial) is in Equation 1 and the model form for LDW (logistic regression) is in Equation 2.

$$\log\left(\frac{P(s_{ij}=y)}{P(s_{ij}=\text{"Far"})}\right) = \beta_y x_{ij} + \varepsilon_i \quad (1)$$

where s = system setting, i = cluster (month in vehicle), j = individual trip

$$\log\left(\frac{P(s_{ij}=\text{"Off"})}{P(s_{ij}=\text{"On"})}\right) = \beta x_{ij} + \varepsilon_i \quad (2)$$

where s = system setting, i = cluster (month in vehicle), j = individual trip

Predictor candidates were:

- Trip distance (miles),
- Day/Night status at the end of the trip (differentiated by civil dusk),
- Fraction of trip at high speeds (55mph+),
- Odometer (miles; linear and quadratic or logarithmic),
- Age (years),
- Gender,
- Vehicle Model, and
- HUD presence.

Each vehicle's odometer is treated as the time variable, allowing for different drivers to accumulate experience with the system at different rates over the course of the study. Two-way interactions between effects with significant main effects were also considered for the model.

Modeling was done in SAS using GEE in Proc GENMOD. To define clustering, the data were organized by month nested within each vehicle. The month component was included to account for climate and other time affected variables that were not directly captured by the odometer reading.

Piecewise odometer models were considered in addition to the linear-quadratic and logarithmic scaling. These piecewise models were constructed using both scaling methods, and transition points from 8,000 to 14,000 miles were considered. Candidate models were compared using the Quasi-AIC (QIC) calculated by SAS. The smallest QIC of the models considered was achieved for odometer on the logarithmic scale with a piecewise structure at 10,850 miles. This is consistent with the observed trends and was used in the final LDW model.

Constraints (filtering): The BQ1/AQ2 analysis does not meaningfully restrict the data except in situations where there are incomplete records.

Results - FCA: Table 30 shows the multinomial model for FCA setting, which consists of three sub-models that describe the odds of setting the FCA to one of the other three settings as opposed to Far. Positive coefficients indicate an increase in settings other than Far. Only significant effects and main effects that are components of interactions were retained in the model. The main effect of vehicle model indicated differences between each of the models, including the two Cadillacs ($z = -2.51$, $p=0.0120$). Thus, all three vehicle models were included in the interaction terms as well. However, for the interaction terms, the Cadillacs do not differ from each other; instead the significant interactions are driven by differences between the Equinox and the Cadillacs.

Table 30 GEE multinomial model of FCA trip setting choice as a function of trip, vehicle, and demographic predictors

	Off versus Far (ref.)				
Effect	Coefficient	Std. Error	EXP(Coef.)	z-score	p-value
Intercept	-0.5186	0.1714	0.5954	-3.03	0.0025
EndOdometer/5,000	0.1734	0.0214	1.1893	8.08	<.0001
(EndOdometer/5,000)**2	-0.0070	0.0009	0.9930	-8.09	<.0001
Fraction of Trip at 55mph+	-0.2806	0.055	0.7553	-5.1	<.0001
Age	-0.0219	0.0021	0.9783	-10.67	<.0001
Gender - Male					
VehicleModel - SRX	-1.0779	0.2002	0.3403	-5.38	<.0001
VehicleModel - XTS	-0.5043	0.1948	0.6039	-2.59	0.0096
Trip Distance (miles)					
HUD Available - Yes	-5.232	0.8887	0.0053	-5.89	<.0001
Night - Sun Elev. < -6	0.0674	0.0334	1.0697	2.02	0.0433
Linear Odometer * SRX	-0.1019	0.0388	0.9031	-2.63	0.0086
Linear Odometer * XTS	-0.1578	0.0322	0.8540	-4.9	<.0001
Quad. Odometer * SRX	0.0041	0.0016	0.0041	2.57	0.0103
Quad. Odometer * XTS	0.0064	0.0011	1.0064	5.56	<.0001
Age * HUD	0.0729	0.0127	1.0756	5.75	<.0001
Night * SRX	-0.3175	0.0662	0.7280	-4.8	<.0001
Night * XTS	-0.2788	0.0687	0.7567	-4.06	<.0001

	Near versus Far (ref.)				
Effect	Coefficient	Std. Error	EXP(Coef.)	z-score	p-value
Intercept	-0.8971	0.1311	0.4078	-6.84	<.0001
EndOdometer/5,000	0.0188	0.0040	1.0190	4.66	<.0001
(EndOdometer/5,000)**2					
Fraction of Trip at 55mph+					
Age	-0.0072	0.0019	0.9928	-3.86	0.0001
Gender - Male					
VehicleModel - SRX	-1.3216	0.064	0.2667	-20.66	<.0001
VehicleModel - XTS	-0.922	0.0581	0.3977	-15.86	<.0001
Trip Distance (miles)					
HUD Available - Yes					
Night - Sun Elev. < -6					
	Medium versus Far (ref.)				
Effect	Coefficient	Std. Error	EXP(Coef.)	z-score	p-value
Intercept	-0.7435	0.1204	0.4754	-6.18	<.0001
EndOdometer/5,000	0.0644	0.0105	1.0665	6.13	<.0001
(EndOdometer/5,000)**2	-0.0024	0.0004	0.9976	-5.97	<.0001
Fraction of Trip at 55mph+	-0.1842	0.0415	0.8318	-4.44	<.0001
Age	-0.0044	0.0015	0.9956	-2.84	0.0045
Gender - Male					
VehicleModel - SRX	-0.8371	0.0476	0.4330	-17.59	<.0001
VehicleModel - XTS	-0.7282	0.0491	0.4828	-14.84	<.0001
Trip Distance (miles)					
HUD Available - Yes					
Night - Sun Elev. < -6					

To illustrate, Figure 48 through Figure 50 show the modeled effect of odometer on FCA setting. These plots assume the following: Female driver, average prop. over 55 mph (0.08), avg. age by vehicle (Equ: 58, SRX: 60, XTS: 66), avg. LDW count (4), trip ends before dusk.

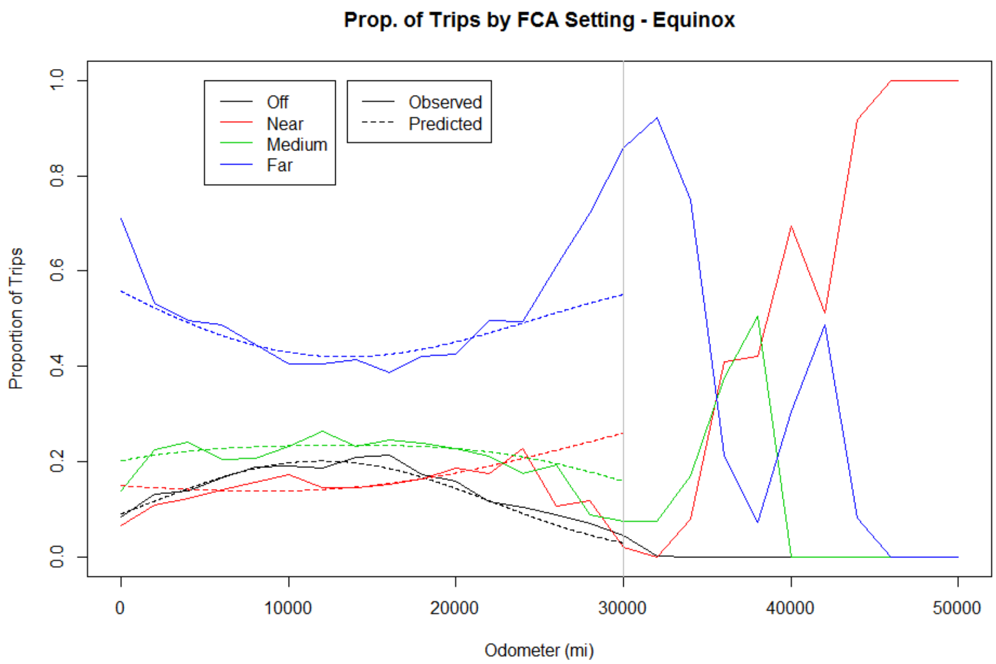

Figure 48. Modeled and observed proportion of trips in each FCA setting by odometer for Equinox.

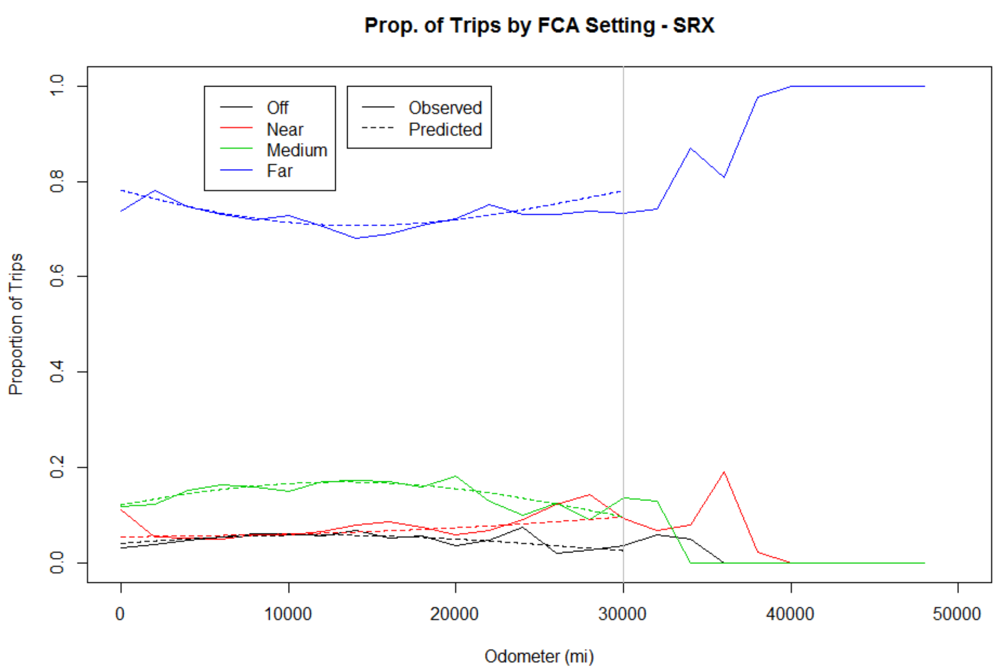

Figure 49. Modeled and observed proportion of trips in each FCA setting by odometer for SRX.

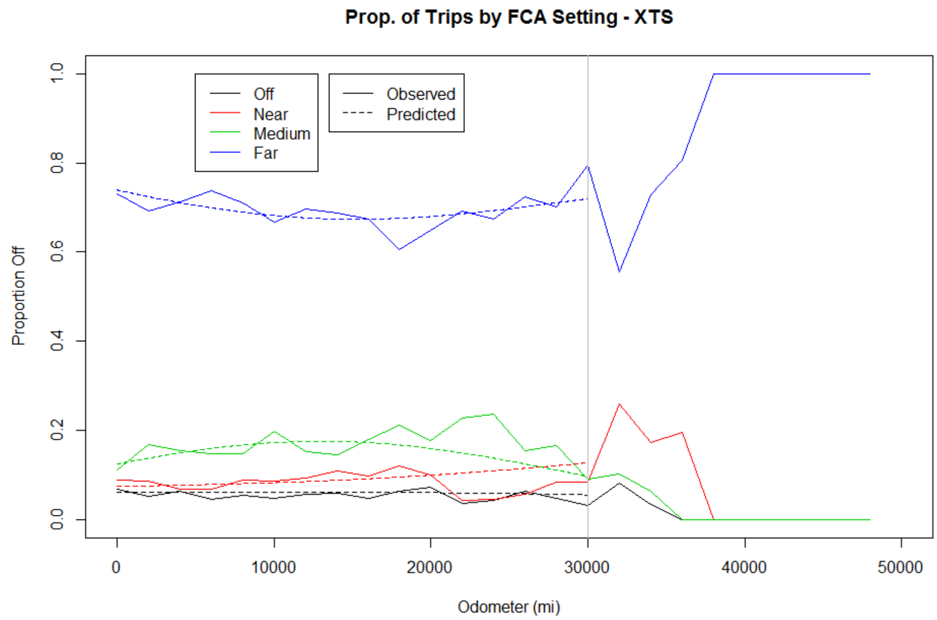

Figure 50. Modeled and observed proportion of trips in each FCA setting by odometer for XTS.

Results – LDW: The GEE model for LDW is shown in Table 31. Positive coefficients indicate increasing probability of turning the system Off.

Table 31 GEE model coefficients and significance tests predicting LDW predominantly Off for a given trip

Effect	Coefficient	Std. Error	EXP(Coef.)	z-score	p-value
Intercept	-3.4146	0.3913	0.0329	-8.73	<.0001
log(End Odometer) : 0-N	0.5473	0.0432	1.7286	12.66	<.0001
log(End Odometer) : N+					
Fraction of Trip at 55mph+	-0.517	0.0477	0.5963	-10.83	<.0001
LDW Alerts on Trip	0.0377	0.0012	1.0384	30.14	<.0001
Age	-0.0088	0.0012	0.9912	-7.45	<.0001
Gender - Male	-0.1138	0.0563	0.8924	-2.02	0.0432
VehicleModel - SRX	0.5333	0.5385	1.7045	0.99	0.322
VehicleModel - XTS	2.3198	0.5007	10.1736	4.63	<.0001
Trip Distance (miles)	-1.4988	0.0654	0.2234	-22.9	<.0001
HUD Available - Yes	0.1311	0.0444	1.1401	2.95	0.0031
Night - Sun Elev. < -6	0.1708	0.0268	1.1863	6.36	<.0001
Early Odometer * SRX	-0.2331	0.0613	0.7921	-3.8	0.0001
Early Odometer * XTS	-0.4061	0.057	0.6662	-7.13	<.0001
Night * SRX	-0.2404	0.0373	0.7863	-6.45	<.0001
Night * XTS	-0.1263	0.0365	0.8814	-3.46	0.0005
Gender - Male * SRX	0.2941	0.0763	1.3419	3.85	0.0001
Gender - Male * XTS	0.2315	0.0732	1.2605	3.16	0.0016

To illustrate, Figure 51 shows the modeled effect of odometer on LDW Off setting. This plots assume the following: Female driver, average prop. over 55 mph (0.08), avg. age by vehicle (Equ: 58, SRX: 60, XTS: 66), avg. LDW count (4), trip ends before dusk.

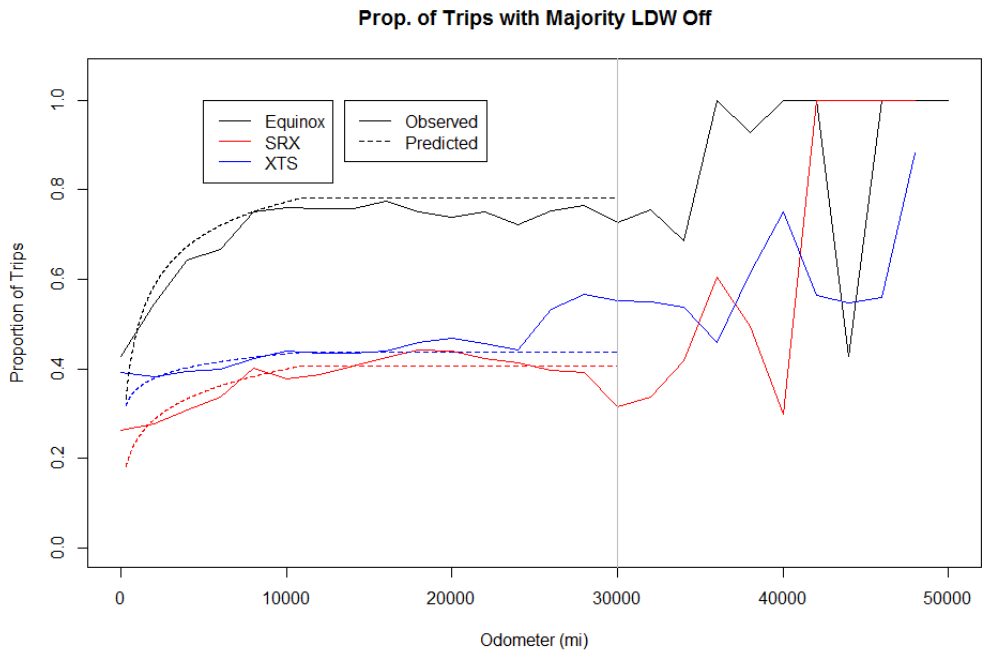

Figure 51. Modeled and observed proportion of LDW off by odometer.

BQ2: How does the system setting vary by distribution of normal driving behavior (in terms of speed, following distance, etc.)?

Method*:* The normal driving statistics were created using the available counter data collected by the OnStar system over the course of the study. These counters were aggregated over the entire course of the study giving one value per counter per individual. These counters were then used to create a number of descriptive statistics to describe driving behavior. These were:

- Proportion of time over left lane boundary,[4]
- Proportion of time over right lane boundary,[5]
- Proportion of time driving under 35 mph (reference), between 35 mph and 55 mph or over 55 mph,

[4] Calculated as proportion of the time when lane boundary confidence is high that the center of the vehicle is within 1m of the left lane boundary.

[5] Calculated as proportion of the time when lane boundary confidence is high that the center of the vehicle is within 1m of the right lane boundary.

- Proportion of time following another vehicle,
- Average follow distance when following,[6]
- Average monthly miles, and
- Preferred haptic setting (on/off).

The normal driving statistics were standardized to increase interpretability of effect sizes. Additional demographic information was used for prediction, including driver age and gender, vehicle model and HUD availability.

The response was assumed to be multinomial (FCA) or binomial (LDW) with the number of trips taken serving as the exposure. Each trip is categorized according to the dominant FCA and LDW setting over the course of the trip, creating the response.

The multinomial (FCA) model form is shown in Equation 3 and the binomial (LDW) form is shown in Equation 4.

$$\log\left(\frac{P(s_i=y)}{P(s_i=\text{"Far"})}\right) = \beta_y x_i \quad (3)$$

where s = system setting and i = vehicle

$$\log\left(\frac{P(s_i=\text{"Off"})}{P(s_i=\text{"On"})}\right) = \beta x_i \quad (4)$$

where s = system setting and i = vehicle

Constraints (filtering): There was no substantial filtering for BQ2, except where required by the unavailability of data.

[6] Calculated using histogram data collected by OnStar. The center-point of each histogram bin was used to determine the 'distance' value for the time spent in that bin.

Results - FCA: The FCA model, shown in Table 32, consists of three sub-models. Positive coefficients indicate a greater probability of using settings other than Far (specific setting depends on the sub-model).

Table 32 GEE multinomial model of FCA trip setting choice as a function of normal-driver predictors

	Off versus Far (ref)				
Parameter	Coefficient	Std. Error	Exp(Coef.)	Wald Chi-sq.	p-value
Intercept	-0.0883	0.2806	0.9155	0.0991	0.7529
Prop. Following					
Age	-0.0173	0.0048	0.9828	12.9530	0.0003
SRX/XTS	-1.3454	0.1372	0.2604	96.1210	<.0001
Willliam's Method - Scale	0.834001				
	Near versus Far (ref)				
Parameter	Coefficient	Std. Error	Exp(Coef.)	Wald Chi-sq.	p-value
Intercept	-0.3734	0.2684	0.6884	1.9355	0.0164
Prop. Following					
Age	-0.0115	0.00451	0.9886	6.5332	0.0106
Model SRX	-1.3429	0.1583	0.2611	71.9695	<.0001
Model XTS	-0.8097	0.1465	0.4450	30.5378	<.0001
Willliam's Method - Scale	0.805968				
	Medium versus Far (ref)				
Parameter	Coefficient	Std. Error	Exp(Coef.)		
Intercept	-0.5717	0.0762	0.5646	56.2876	<.0001
Prop. Following	0.2623	0.0744	1.2999	12.4356	0.0004
Age					
SRX/XTS	-0.9062	0.1001	0.4041	81.8992	<.0004
Prop. Fol. * Haptic Avail	-0.2789	0.1003	0.7566	7.7235	0.0055
Willliam's Method - Scale	0.765724				

Results - LDW: The LDW model is shown in Table 33. Positive coefficients indicate increased tendency to turn the system Off.

Table 33 GEE model coefficients and significance tests predicting LDW predominantly Off for a trip based on normal-driving descriptors at the vehicle level

Using Available Alert Options + Interactions					
Parameter	Coefficient	Std. Error	Exp(Coef.)	Wald Chi-sq.	p-value
Intercept	0.7291	0.0677	2.0732	116.045	<.0001
Over Left Lane Prop.					
Over Right Lane Prop.	0.3624	0.0764	1.4368	22.4876	<.0001
Prop. Speed in 35-55	0.3914	0.0743	1.4791	27.7826	<.0001
Prop. Speed 55+					
Prop. Following					
Avg. Follow Dist.	-0.0899	0.0385	0.9140	5.4685	0.0194
Avg. Monthly Miles	0.3490	0.0642	1.4176	29.586	<.0001
Gender - Male					
SAS - Available	-0.6858	0.1631	0.5037	17.6831	<.0001
HUD - Available	0.2267	0.1106	1.2545	4.2007	0.0404
Alert Setting - SAS	-0.6372	0.1533	0.5288	17.2862	<.0001
Over Left * SAS					
Over Right * SAS	-0.2863	0.0907	0.7510	9.9586	0.0016
Prop Speed 35-55*SAS	-0.3348	0.0891	0.7155	14.1094	0.0002
Avg. Mon. Mi * SAS	-0.2526	0.0808	0.7768	9.782	0.0018
Williams Method – Scale	0.614971				

BQ3/AQ1: (BQ3) How do alert rates vary by condition (e.g., light/dark, speed) and setting? (AQ1) How do alert rates change over time within-vehicle?

Method*:* For LDW, the investigation of alert rate was performed at the trip level, and focused on FCA imminent collision alerts and LDW alerts (to the left and right jointly). The rate was modeled using a Poisson rate model taking the trip distance in hundreds of miles as the exposure.

The model form is shown in Equation 5.

$$\log\left(\frac{\mu_{ij}}{d_j}\right) = \log(\lambda_{ij}) = \beta x_{ij} + \varepsilon_i$$

$$Alerts_{ij} \sim Pois(d_j \lambda_{ij}), i.e., \mu_{ij} = \lambda_{ij} d_j \qquad (5)$$

where i = cluster (month in vehicle), j = trip, d = trip distance

For modeling individual FCA alert categories, the number of alerts of each type were aggregated over each month of the study. This data was then regressed for each vehicle. Exposure was evaluated in the same way as the initial modeling.

Constraints (filtering): Any trips that were less than 1 mile (Ending Odometer - Starting Odometer) were omitted.

Results - FCA: The Poisson model of FCA alert rate is shown in Table 34. Positive coefficients are associated with increases in alert rate.

Table 34 Model parameters for Poisson model of FCA alert rate.

Parameter	Estimate	Std. Error	EXP(Coef.)	Z - Score	P-Value
Intercept	3.7317	0.1106	41.7500	33.74	<.0001
Log (Odometer)	-0.2275	0.0114	0.7965	-19.90	<.0001
Vehicle Model - XTS	0.4757	0.0285	1.6091	16.69	<.0001
Vehicle Model - SRX	0.3236	0.0231	1.3821	14.04	<.0001
Age	-0.0274	0.0006	0.9730	-43.64	<.0001
Night = Sun Elev. <= -6 deg	-0.3688	0.0148	0.6916	-24.85	<.0001
Prop. Trip > 55 mph					
FCA Setting - Off	-0.4994	0.2624	0.6069	-1.90	0.057
FCA Setting - Near	-0.7271	0.0276	0.4833	-26.32	<.0001
FCA Setting - Medium	-0.2872	0.0227	0.7504	-12.65	<.0001
HUD	-0.1164	0.0284	0.8901	-4.10	<.0001
Gender - Male	0.246	0.0186	1.2789	13.23	<.0001
ln Odometer * Off	0.0835	0.0288	1.0871	2.89	0.0038
Model XTS * FCA - Off	-0.2657	0.0488	0.7667	-5.45	<.0001
Model XTS * FCA - Near					
Model XTS * FCA - Mid					
Model SRX * FCA - Off	-0.2891	0.0483	0.7489	-5.99	<.0001
Model SRX * FCA - Near					
Model SRX * FCA - Mid					

Results - LDW: The Poisson model of LDW alert rate is shown in Table 35. Positive coefficients are associated with increases in alert rate.

Table 35 Model parameters for Poisson model of LDW alert rate.

Parameter	Estimate	Std. Error	EXP(Coef.)	Z-value	p-value
Intercept	2.5655	0.1372	13.0072	18.70	<.0001
LOG(Odometer)	0.1271	0.0153	1.1355	8.33	<.0001
Vehicle Model - SRX	-0.1639	0.1569	0.8488	-1.04	0.2962
Vehicle Model - XTS	0.3153	0.1659	1.3707	1.90	0.0573
Age / 10					
Gender - Male					
Prop. Trip > 55 mph	-0.1315	0.0108	0.8768	-12.12	<.0001
Night (Sun Elev. <= -6 deg)	0.0218	0.0058	1.0220	3.74	0.0002
LDW Setting - Off	0.8606	0.1287	2.3646	6.69	<.0001
HUD	-0.0535	0.018	0.9479	-2.97	0.003
Log Odometer * LDW Off	-0.032	0.0142	0.9685	-2.25	0.0243
Model - SRX * LDW Off	-0.2708	0.0228	0.7628	-11.89	<.0001
Model - XTS * LDW Off	-0.3465	0.0231	0.7072	-14.99	<.0001
Log Odo. * Model - SRX	0.0404	0.0175	1.0412	2.31	0.0209
Log Odo. * Model - XTS	-0.0361	0.0185	0.9645	-1.95	0.0509

BQ4: What is the overall distribution of Post-Alert Braking Time ? How does PABT vary by condition (e.g., road type, light/dark, speed) and setting?

PABT is measured to within 50 milliseconds and is captured at initial brake travel. This time does not necessarily represent a response to the alert itself; it instead more accurately represents a response that occurred after the alert was issued. In some cases, no braking may occur.

Method: Linear mixed models were used to model PABT, which was transformed logarithmically to improve normality of the residuals. Predictors included: setting, road type, speed at event, wiper state, following distance at event, night/day, vehicle model, HUD, SAS, scenario, age, gender, and odometer. Age, gender, and odometer were not significant in this model. Interactions were explored and three were significant: setting X SAS, following distance X road type, and following distance X scenario.

The linear mixed model form is shown in Equation 6.

$$\log(y_{ij}) = \beta x_{ij} + \varepsilon_i + \varepsilon_{ij} \quad (6)$$

where i = vehicle, j = alert

Constraints (filtering): The events are identified by searching through the data for episodes in which the constraints in Table 36 apply.

Table 36 Analysis Constraints

Constraints
1. Post-Alert Brake Reaction Time between 0.4 to 3 s
2. Imminent alerts
3. No LDW warning at the same time.
4. Acceleration On at event
5. Lead vehicle ahead
6. Same lead vehicle (Part – 2)
7. Stopped or slowing lead vehicle (Part – 2)

Results: The mixed model of log PABT is shown in Table 38 with least squares means of categorical predictors shown in Table 38. Note that means shown are in log units.

Table 37 Predictors of Post-Alert Braking Time

Type 3 Tests of Fixed Effects				
Effect	**Num DF**	**Den DF**	**F Value**	**Pr > F**
Setting	3	12E3	11.05	<.0001
Road Type	4	12E3	4.42	0.0014
Speed at Event	1	12E3	338.11	<.0001
Wiper	1	12E3	10.12	0.0015
Following Distance at Event	1	12E3	4.08	0.0435
Night	1	12E3	25.47	<.0001
Vehicle Model	2	12E3	6.35	0.0018
Head-Up Display	1	12E3	6.54	0.0106
Setting*SAS	3	12E3	4.86	0.0022
SAS	1	12E3	1.04	0.3088
Following Distance*Road Type	4	12E3	2.56	0.0369
FCA Scenario	6	12E3	11.15	<.0001
Following Distance*FCA Scenario	6	12E3	3.58	0.0015

Table 38 Least squares means for model of PABT

Effect	Variable Level	Variable Level	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept			-0.08732	0.06005	1659	-1.45	0.1461
Setting	Off		0.03883	0.02879	12E3	1.35	0.1774
Setting	Near		0.0405	0.03165	12E3	1.28	0.2008
Setting	Medium		-0.00874	0.01741	12E3	-0.5	0.6159
Setting	Far		0	.	.	.	.
Road Type	Interstate		-0.1437	0.04188	12E3	-3.43	0.0006
Road Type	Principal Arterial-Freeways and Expressways		-0.1664	0.04811	12E3	-3.46	0.0005
Road Type	Principal Arterial-Other		-0.122	0.03535	12E3	-3.45	0.0006
Road Type	Minor Arterial		-0.1083	0.03809	12E3	-2.84	0.0045
Road Type	Major Collector		0	.	.	.	.
Speed MPH_MPH			0.008379	0.000398	12E3	21.05	<.0001
Wiper	Wiper Off		-0.1575	0.04695	12E3	-3.35	0.0008
Wiper	Wiper On		0	.	.	.	.
Following Distance			0.004107	0.001314	12E3	3.13	0.0018
Time of Day	Day		-0.07181	0.01275	12E3	-5.63	<.0001
Time of Day	Night		0	.	.	.	.
Vehicle Model	Equinox		-0.09632	0.02502	12E3	-3.85	0.0001
Vehicle Model	SRX		-0.0443	0.01434	12E3	-3.09	0.002
Vehicle Model	XTS		0	.	.	.	.
HUD	Head-up display Off		-0.04248	0.01792	12E3	-2.37	0.0178
HUD	Head-up display On		0	.	.	.	.
Setting*Alert Type	Off	Chime	0.09597	0.04059	12E3	2.36	0.0181
Setting*Alert Type	Off	Haptic	0	.	.	.	.
Setting*Alert Type	Near	Chime	-0.07062	0.04851	12E3	-1.46	0.1455
Setting*Alert Type	Near	Haptic	0	.	.	.	.
Setting*Alert Type	Medium	Chime	-0.03403	0.03247	12E3	-1.05	0.2946
Setting*Alert Type	Medium	Haptic	0	.	.	.	.

Setting*Alert Type	Far	Chime	-0.04912	0.02132	12E3	-2.3	0.0212
Setting*Alert Type	Far	Haptic	0	.	.	.	.
Alert Type	Chime		0	.	.	.	.
Alert Type	Haptic		0	.	.	.	.
Following Distance*Road Type	Interstate		0.001645	0.001769	12E3	0.93	0.3523
Following Distance*Road Type	Principal Arterial-Freeways and Expressways		0.002756	0.002006	12E3	1.37	0.1694
Following Distance*Road Type	Principal Arterial-Other		0.002444	0.001484	12E3	1.65	0.0997
Following Distance*Road Type	Minor Arterial		0.004774	0.001595	12E3	2.99	0.0028
Following Distance*Road Type	Major Collector		0	.	.	.	.

A second model focused on two scenarios: LV slowing or stopped and remaining after 4 seconds. This model is shown in Table 39 with least squares means shown in Table 40.

Table 39 Predictors of Post Alert Braking Time for FCA imminent alert scenarios when LV is estimated to be slowing or stopped

Type 3 Tests of Fixed Effects				
Effect	**Num DF**	**Den DF**	**F Value**	**Pr > F**
Setting	3	1182	4.6	0.0033
Road Type	4	1182	1.59	0.1744
Following Distance	1	1182	0.28	0.599
Night	1	1182	23.77	<.0001
Vehicle Model	2	1182	5.87	0.0029
Following Distance*Road Type	4	1182	2.79	0.0252

Table 40 Predictors of Post Alert Braking Time for FCA imminent alert

Effect	Variable Level	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept		-0.1442	0.08616	903	-1.67	0.0945
Setting	Off	0.1018	0.03515	1182	2.9	0.0039
Setting	Near	-0.01337	0.0533	1182	-0.25	0.8019
Setting	Medium	-0.05276	0.02848	1182	-1.85	0.0642
Setting	Far	0	.	.	.	.
Road Type	Interstate	-0.07094	0.1131	1182	-0.63	0.5305
Road Type	Principal Arterial-Freeways and Expressways	0.1204	0.1427	1182	0.84	0.3992
Road Type	Principal Arterial-Other	-0.1237	0.08927	1182	-1.39	0.1661
Road Type	Minor Arterial	-0.1494	0.09607	1182	-1.55	0.1203
Road Type	Major Collector	0	.	.	.	.
Following Distance		-0.0006	0.003642	1182	-0.17	0.8681
Time of Day	Day	-0.146	0.02996	1182	-4.88	<.0001
Time of Day	Night	0	.	.	.	.
Vehicle Model		-0.07818	0.02581	1182	-3.03	0.0025
Vehicle Model		-0.06473	0.02255	1182	-2.87	0.0042
Vehicle Model		0	.	.	.	.
Following Distance*Road Type	Interstate	0.000427	0.005327	1182	0.08	0.9361
Following Distance*Road Type	Principal Arterial-Freeways and Expressways	-0.00731	0.006744	1182	-1.08	0.2784
Following Distance*Road Type	Principal Arterial-Other	0.004713	0.004111	1182	1.15	0.2518
Following Distance*Road Type	Minor Arterial	0.009643	0.004419	1182	2.18	0.0293
Following Distance*Road Type	Major Collector	0	.	.	.	.

BQ5: What is the rate of driver non-response to FCA alerts?

Method: Non-response is defined as the absence of a post-alert braking response within 3 sec. It is considered as a binary outcome in which 0=Response and 1=Non Response. The unit of analysis is the alert, and only those alerts with the system on (at any setting) were considered for analysis. Constraints are listed in Table 41.

Table 41 Constraints of non-response analysis

Constraints
1. FCA Setting – Near, Medium and Far
2. No LDW warning at the same time.
3. Imminent Alerts
4. Brake Pedal Off
5. Acceleration Pedal On
6. Presence of lead vehicle
7. Brake Pedal timing <=0.4 and 3<tb.

Probability of non-response was modeled using logistic regression (see Equation 7).

$$\log\left(\frac{P(r_j=\text{"No Resp."})}{P(r_j=\text{"Resp."})}\right) = \beta x_j \tag{7}$$

where j = alert

Results: The significant predictors in the logistic regression model are shown in Table 42. The odds ratios and confidence intervals are given in Table 43.

Table 42 Model parameters and tests of significance for logistic regression modeling probability of non-response to FCA alerts.

Effect	**DF**	**Wald Chi-Square**	**Pr > ChiSq**
Setting	2	67.5031	<.0001
Following Distance	1	4.5661	0.0326
Road Type	4	10.0223	0.0401
HUD	1	10.4242	0.0012
Night	1	69.0541	<.0001
Vehicle Model	2	29.7600	<.0001
LV State	4	3188.6365	<.0001
Following Distance X Road Type	4	25.6031	<.0001

Table 43 Odds ratios for logistic regression model of non-response to FCA imminent alerts

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
Setting Medium vs. Far	1.166	1.085	1.254
Setting Near vs. Far	1.565	1.393	1.758
HUD Head-up display On vs. Head-up display Off	1.146	1.055	1.244
Time of Day Day vs. Night	1.461	1.336	1.598
Vehicle Model Equinox vs. XTS	1.071	0.985	1.165
Vehicle Model SRX vs. XTS	0.885	0.829	0.945
Lead vehicle State Oncoming vs. Accelerating	1.754	1.536	2.003
Lead vehicle State Slowing vs. Accelerating	0.200	0.178	0.226
Lead vehicle State Stopped vs. Accelerating	0.272	0.088	0.843
Lead vehicle State Unknown vs. Accelerating	3.334	3.154	3.523

BQ8: How does driver response (PABT) differ when the system is "on" versus "off" (i.e., the driver is alerted or not)?

This analysis is very similar to BQ4, but the data were recoded such that near, medium and far settings were all treated as On. A linear mixed model was run at the alert level. Vehicle, is treated as a random effect. The form of the linear mixed model is shown in Equation 8.

$$\log(y_{ij}) = \beta x_{ij} + \varepsilon_i + \varepsilon_{ij} \tag{8}$$

where i = vehicle, j = alert

Table 44 shows the significant model predictors, along with test values, and Table 45 shows the least squares means for all categorical effects.

Table 44 Model of PABT with system on or off

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
Setting	1	11711	49.11	<.0001
Road Type	4	11711	4.2	0.0021
Wiper	1	11711	11.18	0.0008
Speed MPH	1	11711	453.43	<.0001
Following Distance	1	11711	137.7	<.0001
Vehicle Model	2	11711	29.44	<.0001
HUD	1	11711	5.8	0.0161
Time of Day	1	11711	32.16	<.0001
Setting*Time of Day	1	11711	8.72	0.0032
Following Distance*Road Type	4	11711	2.61	0.0337

Table 45 Least squares means for PABT model with system on versus off

Predictor	Variable Level	Variable Level	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept			-0.1034	0.06015	1659	-1.72	0.0859
Setting	OFF		0.2433	0.0441	11711	5.52	<.0001
Setting	ON		0	.	.	.	.
Road Type	Interstate		-0.1446	0.04188	11711	-3.45	0.0006
Road Type	Principal Arterial-Freeways & Expressways		-0.1678	0.0481	11711	-3.49	0.0005
Road Type	Principal Arterial-Other		-0.1227	0.03535	11711	-3.47	0.0005
Road Type	Minor Arterial		-0.1095	0.0381	11711	-2.87	0.0041
Road Type	Major Collector		0	.	.	.	.
Wiper	Wiper Off		-0.157	0.04695	11711	-3.34	0.0008
Wiper	Wiper On		0	.	.	.	.
Speed MPH			0.0084	0.0004	11711	21.29	<.0001
Following Distance			0.00402	0.00131	11711	3.06	0.0022
Vehicle Model	Equinox		-0.1211	0.0163	11711	-7.43	<.0001
Vehicle Model	SRX		-0.0418	0.01439	11711	-2.91	0.0037
Vehicle Model	XTS		0	.	.	.	.
HUD	OFF		-0.0434	0.01801	11711	-2.41	0.0161
HUD	ON		0	.	.	.	.
Time of Day	Day		-0.0618	0.01332	11711	-4.64	<.0001
Time of Day	Night		0	.	.	.	.
Setting*Time of Day	OFF	Day	-0.1339	0.04535	11711	-2.95	0.0032
Setting*Time of Day	OFF	Night	0	.	.	.	.
Setting*Time of Day	ON	Day	0	.	.	.	.
Setting*Time of Day	ON	Night	0	.	.	.	.
Following Distance*Road Type	Interstate		0.00171	0.00177	11711	0.97	0.3325
Following Distance*Road Type	Principal Arterial-Freeways & Expressways		0.0029	0.00201	11711	1.45	0.1484
Following Distance*Road Type	Principal Arterial-Other		0.00248	0.00148	11711	1.67	0.0946
Following Distance*Road Type	Minor Arterial		0.00482	0.0016	11711	3.02	0.0025
Following Distance*Road Type	Major Collector		0	.	.	.	.

The analysis was also repeated using two scenarios: Approaching slowing vehicle and approaching stopped vehicle (target remains after 4 s). Significant parameters are shown in Table 46 and least squares means are shown in Table 47.

Table 46 Model parameters for model of PABT including only in-path approaching slowing vehicle and approaching stopped vehicle scenarios

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
Setting	1	1201	10.32	0.0013
Road Type	4	1201	1.56	0.1819
Following Distance	1	1201	0.24	0.6208
Vehicle Model	2	1201	6.2	0.0021
Time of Day	1	1201	23.25	<.0001
Following Distance*Road Type	4	1201	2.91	0.0207

Setting (On vs. Off) is still significant. However, wiper, road type, HUD, following distance and speed seem to have no effect on post-alert braking time.

In both cases with all scenarios and only the presence of lead vehicle, it is observed that the vehicles that have the setting turned off have a late response to the alert. The brake reaction time after these vehicles receive the alert is still larger compared to the vehicles that have the system turned on.

Table 47 Least squares means of predictors in two-scenario model using setting on versus off

Effect	Variable Level	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept		-0.1569	0.08522	908	-1.84	0.0659
Setting	OFF	0.1107	0.03447	1201	3.21	0.0013
Setting	ON	0	.	.	.	.
Road Type	Interstate	-0.05799	0.1117	1201	-0.52	0.6038
Road Type	Principal Arterial-Freeways and Expressways	0.116	0.1421	1201	0.82	0.4147
Road Type	Principal Arterial-Other	-0.1194	0.08815	1201	-1.35	0.1757
Road Type	Minor Arterial	-0.1479	0.09494	1201	-1.56	0.1195
Road Type	Major Collector	0	.	.	.	.
Following Distance		-0.00048	0.003591	1201	-0.13	0.8943
Vehicle Model	Equinox	-0.08101	0.02541	1201	-3.19	0.0015
Vehicle Model	SRX	-0.06419	0.02235	1201	-2.87	0.0041
Vehicle Model	XTS	0	.	.	.	.
Time of Day	Day	-0.1421	0.02948	1201	-4.82	<.0001
Time of Day	Night	0	.	.	.	.
Following Distance*Road Type	Interstate	-0.00044	0.005233	1201	-0.08	0.933
Following Distance*Road Type	Principal Arterial-Freeways and Expressways	-0.00708	0.006706	1201	-1.06	0.2912
Following Distance*Road Type	Principal Arterial-Other	0.004495	0.004032	1201	1.12	0.2651
Following Distance*Road Type	Minor Arterial	0.009544	0.004339	1201	2.2	0.028
Following Distance*Road Type	Major Collector	0	.	.	.	.

AQ3: How do alert responses (PABT) change over time and as a function of alert experience?

Method: Alert experience is parameterized using the number of prior alerts and rate of driver response to the alerts occurring in the data collection window. The predictor variable for the analysis is the alert experience, which is estimated using non-response rate in the first two months of the study. The dependent variable used for analysis is the average or median brake response time for the remaining months. Analysis is at the vehicle level. The setting is recoded as Dominant setting, which is the predominant setting the driver prefers during all the trips in the given time frame.

The form of the linear mixed model is shown in Equation 9.

$$y_{ij} = \beta x_{ij} + \varepsilon_i + \varepsilon_{ij} \tag{9}$$

where i = vehicle, j = month

Results: Table 48 shows the model predictors and hypothesis tests. Note that early non-response rate is not significant. Table 49 shows the least squares means of log PABT for the model.

Table 48 Model predictors for regression model of PABT

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
Non-Response Rate (st two months)	1	1363	1.31	0.2517
Dominant FCA Setting	2	1363	4.64	0.0098
HUD	1	1363	4.65	0.0313
Vehicle Model	2	1363	38.15	<.0001

Table 49 Least squares means of log PABT

Effect	Variable Level	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept		0.1496	0.02489	1363	6.01	<.0001
Non-response rate (st two months)		0.02677	0.02335	1363	1.15	0.2517
Dominant FCA Setting	Near	0.07887	0.02645	1363	2.98	0.0029
Dominant FCA Setting	Medium	0.02324	0.01994	1363	1.17	0.244
Dominant FCA Setting	Far	0	.	.	.	.
HUD	No	-0.0559	0.02592	1363	-2.16	0.0313
HUD	Yes	0	.	.	.	.
Vehicle Model	Equinox	-0.1864	0.02278	1363	-8.18	<.0001
Vehicle Model	SRX	-0.0598	0.02154	1363	-2.78	0.0055
Vehicle Model	XTS	0	.	.	.	.

AQ4: How does normal driving behavior change over time and as a function of alert experience?

Method*:* The normal driving statistics were created using the available counter data collected by the OnStar system over the course of the study. These counters were aggregated over the entire course of the study giving one value per counter per individual. These counters were then used to create a number of descriptive statistics to describe driving behavior. Of these, only three were considered likely to change as a function of system setting and exposure.

- Proportion of time over left lane boundary[7]
- Proportion of time over right lane boundary[8]
- Average follow distance when following[9]

[7] Calculated as proportion of the time when lane boundary confidence is high that the center of the vehicle is within 1m of the left lane boundary.

[8] Calculated as proportion of the time when lane boundary confidence is high that the center of the vehicle is within 1m of the right lane boundary.

The proportions were modeled using mixed effects beta models, while the average following distance was modeled using linear mixed effects models. In additional to demographic predictors, the proportion of time spent using each of the settings (calculated by number of dominant trips divided by total trips). Proportion of time on the Far setting was taken as the reference and the others were included as predictors.

The mixed-effects beta model form is shown in Equation 10 and the linear mixed model is as in Equation 11.

$$\log\left(\frac{\mu_{ij}}{1-\mu_{ij}}\right) = \beta x_{ij} + \varepsilon_i \quad (10)$$

where i = vehicle, j = month

$$y_{ij} = \beta x_{ij} + \varepsilon_i + \varepsilon_{ij} \quad (11)$$

where i = vehicle, j = month

Constraints (filtering): No inherent limiting except where required by missing data.

Results – Average Following Distance: Table 50 shows the linear mixed model coefficients and standard errors for average following distance. Positive coefficients indicate an increase in following distance as a function of the predictor.

Table 50 Average Follow Distance Model (Mixed Effects Linear Model):

Modeling: Avg. Follow Distance		
Effect	Coef.	Std. Error
Intercept	22.2748	0.8966
log(Odometer)	0.3756	0.06304
FCA Setting - Mid		
FCA Setting - Near	-3.9962	1.7279
FCA Setting - Off	-0.517	0.2233
Odo * FCA Mid		
Odo * FCA Near	0.4401	0.1926
Odo * FCA Off		
Haptic - Y	-1.2654	0.3101
Age	0.1807	0.01103

Results – Proportion of Time over Left Lane: Table 51 shows the linear mixed model coefficients and standard errors for proportion of time over left lane. Positive coefficients indicate an increase in proportion of time as a function of the predictor.

[9] Calculated using histogram data collected by OnStar. The center-point of each histogram bin was used to determine the 'distance' value for the time spent in that bin.

Table 51 Proportion of Time over Left Lane (Mixed Effects Beta Model):

Modeling: Over Left Lane Prop.			
Effect	Coef.	Std. Error	EXP(Coef)
Intercept	-2.3042	0.1189	0.0998386
log(Odometer)	-0.06412	0.012	0.9378924
LDW Setting - Off	0.6886	0.09891	1.9909263
Odo * LDW Off	-0.05022	0.01093	0.9510202
Model - SRX	0.1499	0.1229	1.1617181
Model - XTS	-0.2952	0.1241	0.7443827
Age	-0.0065	0.000865	0.9935211
Odo * SRX	-0.00479	0.01371	0.9952215
Odo * XTS	0.06116	0.01375	1.063069
LDW Off * SRX	-0.2304	0.03112	0.7942159
LDW Off * XTS	-0.1666	0.03004	0.8465382
Gender - Male			

Results – Proportion of Time over Right Lane: Table 52 shows the linear mixed model coefficients and standard errors for proportion of time over right lane. Positive coefficients indicate an increase in proportion of time as a function of the predictor.

Table 52 Proportion of Time Over Right Lane (Mixed Effects Beta Model):

Modeling: Over Right Lane Prop.			
Effect	Coef.	Std. Error	EXP(Coef)
Intercept	-2.2252	0.06078	0.1080458
log(Odometer)			
LDW Setting - Off	0.16	0.02374	1.1735109
Odo * LDW Off			
Haptic - Yes	-0.04926	0.03156	0.9519336
LDW Off * Haptic	-0.1067	0.02722	0.8987953
Age	-0.00272	0.000971	0.9972837
Gender - Male	-0.0625	0.02596	0.9394131

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