PARTNERSHIP FOR ANALYTICS RESEARCH IN TRAFFIC SAFETY

Real-world Effectiveness of Model Year 2015–2020 Advanced Driver Assistance Systems

November 9, 2022

To learn more about the work of this partnership, visit NHTSA.gov/PARTS

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1 Executive Summary

In 2020, an estimated 2.3 million people were injured in traffic crashes, and 38,824 people were killed on our nation's roadways [1]. Advanced driver assistance systems (ADAS) and automated driving systems (ADS) in motor vehicles hold the potential to reduce traffic crashes, prevent serious injuries, and save thousands of lives on our roadways each year. Given the growing rate at which auto manufacturers are equipping vehicles with ADAS [2], there is an increasing need to study and understand the safety benefits and potential limitations of these technologies.

The Partnership for Analytics Research in Traffic Safety (PARTS) was formed in 2018 as an independent, voluntary data sharing and analysis partnership among automobile manufacturers and the United States Department of Transportation (USDOT) to address this need. The eight automakers currently participating include American Honda Motor Co., Inc., General Motors LLC, Mazda North American Operations, Mitsubishi Motors R&D of America, Inc., Nissan North America, Inc., Stellantis (Fiat Chrysler Automobiles US LLC), Subaru Corporation, and Toyota Motor North America, Inc. The not-for-profit MITRE Corporation (MITRE) operates PARTS as the independent third party; MITRE conducted this study at the direction of and in collaboration with the PARTS partners.

The objective of this analysis was to explore the real-world effectiveness of ADAS features in avoiding system-relevant crashes. It used police-reported crash data and vehicle equipment data contributed by PARTS partners. It drew on data from 93 vehicle models (see Figure 3-1) for model years 2015 to 2020 that crashed in 13 states (see Table 3-1) from January 2016 through August 2021. The recency of the data allowed PARTS to keep pace as new ADAS features are deployed into the marketplace.

This study assessed forward collision warning (FCW), automatic emergency braking (AEB), pedestrian automatic emergency braking (PAEB), lane departure warning (LDW), lane keeping assistance (LKA), and lane centering assistance (LCA). FCW detects potential collisions ahead and provides a warning to the driver, and AEB and PAEB automatically brake to help avoid those collisions or lessen the severity of impact. LDW monitors the vehicle's position within the driving lane and can alert the driver as the vehicle approaches or crosses lane markers, while LKA and LCA provide momentary and ongoing steering support, respectively, to assist the driver in preventing the vehicle from departing the lane.

This study defined system-relevant crashes as front-to-rear crashes for FCW and AEB; frontal crashes with non-motorists for PAEB;[1] and single-vehicle road-departure crashes for LDW, LKA, and LCA (see Section 3.2). This study defined three crash severity groupings and measured ADAS effectiveness for each: All Crashes involving property damage only, an unknown injury level, or an injury of any severity; Injury Crashes involving an injury of any severity including fatality; and Serious Crashes involving a known serious injury or fatality (see

[1] The vast majority (93%) of PAEB-relevant crashes in this study involved a pedestrian; PARTS also included crashes involving non-motorists given that 3 of the 13 states reported these differently (see Section 3.1.2).

Section 2.2). The level of PARTS partner engagement and the scope of data they shared yielded one of the largest and most representative samplings of system-relevant crashes to date.

This study considered contextual factors that can influence ADAS effectiveness (e.g., driver, vehicle, environmental, crash characteristics). This study used quasi-induced exposure – comparing vehicles equipped with the set of ADAS features under study against vehicles without those features – and logistic regression to estimate the reduction in system-relevant crashes due to the presence of the vehicles equipped with ADAS.

This cross-industry analysis included features with a range of capabilities and parameters that vary by original equipment manufacturer (OEM), vehicle model, model year, and even trimline-specific design and specification. When interpreting results, it is important to understand that this attribute-level variability in ADAS implementations is not captured in the data nor accounted for in the analysis. Similarly, this study does not consider the operational design domain (ODD) for a given ADAS feature that defines the limits of that feature's functional capability to operate. This study considers whether a vehicle is equipped with a given ADAS feature at the time of manufacture and not whether that feature was driver-enabled or disabled at the time of crash.

Overall, the analysis found that ADAS features such as FCW and AEB provide substantial safety benefits across a variety of situations; others, such as LDW and LKA, provide some safety benefit; while PAEB requires more data to make estimates of effectiveness.

- This study estimated that all front-to-rear crashes were reduced by about half (49%) when the striking vehicle was equipped with FCW + AEB compared against striking vehicles that were not equipped with either.[2] A similar reduction (53%) was found for injury front-to-rear crashes. A slightly lower rate (42%) was found for serious front-to-rear crashes. Though it is still substantial, when vehicles are equipped with just FCW, the estimated reduction for all front-to-rear crashes is 16% and for injury front-to-rear crashes is 19%. Altogether, this study shows that the combination of warning and active braking reduced more front-to-rear collisions than warnings alone. Due to the significant size and scope of the dataset, this study was able to identify statistically significant differences in effectiveness when considering a variety of driver characteristics and environmental conditions. The study demonstrates that AEB performs extremely well in all conditions, even when roadway, weather, and lighting conditions are not ideal. ADAS can still assist by potentially making the crash less severe, with fewer and less severe injuries.
- This study investigated the effectiveness of PAEB on non-motorist crashes, but this effort is unable to detect an effect for PAEB. This is likely due to limitations in the data (e.g., the limited number of these incidents in crash reports and the lower level of market penetration for PAEB, particularly in older model years).

[2] By convention, this study rounds statistics to the nearest whole digit to preclude the impression that greater precision exists than is supported by the data. Also, by convention, when PARTS studied certain ADAS features as a set (e.g., both FCW and AEB together), this report shows that set with a plus sign (e.g., FCW + AEB).

- This study estimated that LDW + LKA reduced all single-vehicle road-departure crashes by 8% and injury single-vehicle road-departure crashes by 7%. When adding LCA, crashes are reduced by about the same amount (9%). This study did not find other significant results when analyzing injury or serious crashes with these features together, nor did it find significant reduction for LDW alone.

By leveraging the scale of the partnership, PARTS refined the identification and mapping of ADAS features to system-relevant crashes, identified a set of relevant covariates that were helpful in controlling for influential factors and useful in detecting condition-specific effects, and conducted sensitivity analysis with a different control group (angled intersection crashes) to bolster confidence in the results.

Participating partners have recognized the value of these results in addition to the individualized results shared with industry partners that benchmark the ADAS performance of their vehicles against the aggregate of all others in the dataset. PARTS partners plan to proceed with their co-designed research roadmap to close gaps identified with this study, reiterate this study as ADAS deployment continues to increase, as well as expand the research into new areas. In future iterations of ADAS effectiveness analysis, PARTS will seek to incorporate data from additional partners and states to expand the sample sizes and increase the representativeness of the study. OEM partners may provide data from more vehicle models and model years as well as information about OEM-unique implementations of their ADAS features. In addition, PARTS is reviewing other data sources for how they can support and enable future studies.

As a data sharing public-private partnership, PARTS is unique, evolving, and proving out innovative approaches for collaborating on safety. Working together, PARTS can enhance the safety of our roads in the decades to come.

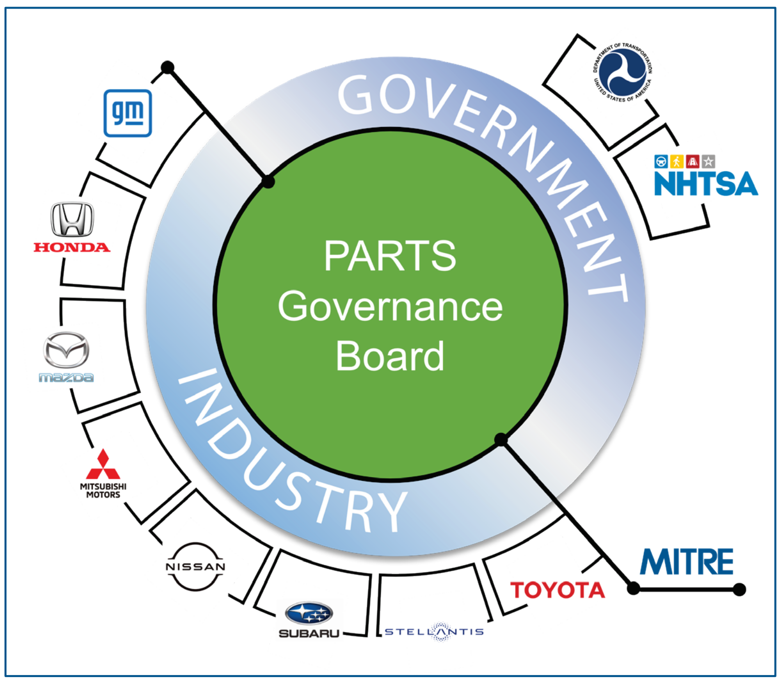
Please see Chapter 2 for more information about PARTS and this study, Chapter 3 for the data and methodology used in this study, Chapter 4 for detailed results, and Chapter 5 for discussion of results, limitations, and potential future research.

2 Background

New safety features and advances in ADAS and ADS promise to reduce the number and severity of traffic crashes, prevent many serious injuries, and save thousands of lives annually. ADAS features are increasingly standard on new vehicles and their adoption is growing. Auto manufacturers (original equipment manufacturers, or OEMs) are equipping their U.S. vehicles with more and more ADAS features over time, including as a mix of both standard and optional equipment. Given the above, there is a need to investigate the real-world performance of these safety features, including their benefits and potential limitations, to drive innovation and continuous improvement.

PARTS was formed to respond to this need through a collaborative data sharing and analysis approach. PARTS combined data from millions of vehicles and crash reports and collaboratively conducted an in-depth analysis to study the overall effectiveness of select ADAS features in reducing fatalities, injuries, and crashes, and the factors that influence their effectiveness. This summary report provides an overview of the background, methodology, data sources, and results from this study.

2.1 PARTS Overview



PARTS is an independent and voluntary partnership among automobile manufacturers and USDOT in which participants share relevant safety-related data solely for collaborative safety analysis. Established in 2018, the goal of this government-industry collaborative, operated by The MITRE Corporation (MITRE), is to gain real-world insights into the safety benefits and opportunities of emerging ADAS and ADS technologies. PARTS partners (see Figure 2-1) co-define the nature of their ongoing data sharing and analysis collaboration.

PARTS operates under its own authority through a legally binding charter and cooperative agreements, shared governance, and consensus-based decision making. Given competitive and regulatory dynamics among partners, PARTS employs an independent third party (ITP) to ensure that partners' interests and sensitive data are protected (e.g., from improper use and disclosure). MITRE fulfills the ITP role for PARTS by serving as a neutral convener and data steward, hosting the collaborative environment and analytic enclave, and performing analyses and studies per partner direction.[3]

The eight participating industry partners that provided vehicle data for this study are American Honda Motor Co., Inc., General Motors LLC, Mazda North American Operations, Mitsubishi Motors R&D of America, Inc., Nissan North America, Inc., Stellantis (FCA US LLC), Subaru Corporation, and Toyota Motor North America, Inc. These PARTS industry partners account for more than 65% of the 2021 U.S. market for sales of passenger cars and light commercial vehicles [3]. Data used for PARTS are governed by binding legal agreements that specify permitted uses and leading privacy and security safeguards. PARTS results are anonymized to ensure that results are not attributed to an individual vehicle or OEM. The large number of PARTS participants allows for larger sample sizes and the potential identification of smaller effects, such as changes in ADAS effectiveness in different conditions.

PARTS studies benefit the public by leveraging this robust dataset to deliver findings that can inform consumer decisions about adopting ADAS safety features. PARTS studies also benefit participating automakers, as each OEM is provided with an analysis of the ADAS effectiveness specific to their vehicle models compared against the aggregate of all others in the dataset. These individualized results provide insights that are not otherwise available to them and can inform their decisions about ADAS improvements.

2.2 ADAS Effectiveness Study Overview

PARTS partners co-designed the partnership's first major study of real-world ADAS effectiveness, which is the subject of this report. As of December 2021, automobile manufacturers submitted vehicle equipment data for approximately 47 million passenger vehicles sold in the United States – representing 93 different models from model years 2015–2020 and covering seven vehicle segments (see Figure 3-1). Vehicle equipment data allows for the identification of ADAS features that were present on the vehicle at the time of its manufacture. MITRE combined this data with police-reported state-level crash data provided by the National Highway Traffic Safety Administration (NHTSA). MITRE, in collaboration with the data-providing partners, then used the combined dataset to analyze the effectiveness of ADAS features per the study parameters the partners defined.

This PARTS study used real-world data to explore the effectiveness of six ADAS features to reduce system-relevant crashes:

1. To what extent do FCW and AEB reduce front-to-rear crashes?
2. To what extent does PAEB reduce frontal non-motorist crashes?
3. To what extent do LDW, LKA, and LCA reduce single-vehicle road-departure crashes?

[3] MITRE is a not-for-profit operator of federally funded R&D centers, works in the public interest, and cannot compete in the commercial marketplace. This charter, coupled with the corporation's analytic and cybersecurity leadership, uniquely positions MITRE to serve data sharing partnerships as a trustee for partners' proprietary and sensitive data, protecting partner equities in a conflict-free manner.

PARTS measured ADAS effectiveness in reducing crashes three ways: (1) in all system-relevant crashes, (2) in system-relevant crashes that had an injury of any severity, (3) in system-relevant crashes that had an injury that was serious or fatal.

PARTS also attempted to determine if a given ADAS feature's effectiveness changed under different conditions (e.g., dark vs. dawn/dusk vs. daylight conditions; different speed limits; dry roads vs. wet roads) and/or for different populations of drivers (e.g., by age) and to quantify the magnitude of those changes in effectiveness if they existed through interactions in the logistic regression models. PARTS included results for key interactions in Chapter 4.

2.2.1 ADAS Features Studied

This study analyzed six ADAS features for system-relevant crashes, as shown in Figure 2-2. These ADAS definitions are primarily based on an industry consortium's standardized names and definitions for these features [2] [4].

ADAS Feature (Acronym) Definition	Visual	System-relevant Crash
Forward Collision Warning (FCW) detects potential collisions ahead and alerts the driver but does not activate the brakes.		Front-to-rear
Automatic Emergency Braking (AEB) detects potential collisions with a vehicle ahead and automatically brakes to help avoid a collision or lessen the severity of impact.		
Pedestrian AEB (PAEB) detects potential collisions with a pedestrian ahead and automatically brakes to help avoid a collision or lessen the severity of an impact.		Non-motorist
Lane Departure Warning (LDW) monitors the vehicle's position within the driving lane and can alert the driver as the vehicle approaches or crosses lane markers.		Single-vehicle road-departure*
Lane Keeping Assistance (LKA) provides momentary steering support to assist the driver in preventing the vehicle from departing the lane (when lanes are clearly marked).		
Lane Centering Assistance (LCA) provides steering support to assist the driver in continuously maintaining the vehicle at or near the center of the lane.		

Figure 2-2 Six ADAS Features Included in this PARTS Study

Note that AEB systems in this study include FCW. Of the PAEB-relevant crashes in this study, 93% involved a pedestrian. PARTS also included frontal crashes involving a non-motorist, which were largely contributed by a few states (Iowa, Texas, and Maryland). These states record crashes involving pedestrians and/or non-motorists differently; some proportion of these recorded non-motorist crashes are likely pedestrian crashes.

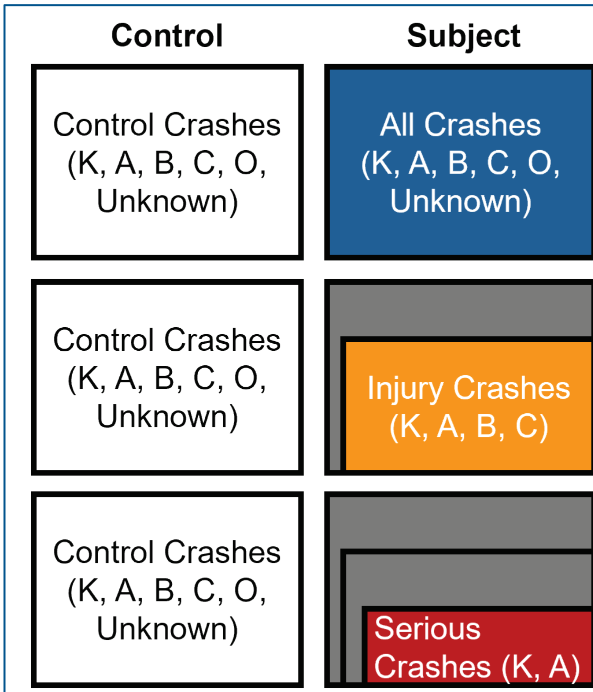
Data limitations did not allow MITRE to isolate which vehicle in a two-vehicle crash initially left its lane. As such, this report focuses on the effectiveness of LDW, LKA, and LCA for single-vehicle road-departure crashes over sideswipe same-direction and opposite-direction crashes.

2.2.2 Injury Structure

PARTS estimated the effectiveness of each ADAS feature for three nested sets of crash types based on the severity of injury of any participant in the crash. This nesting uses injury data recorded in the crash data based on KABCO scores (Figure 2-3) [5]. The sets are as follows:

- **All Crashes:** System-relevant crashes that involve property damage only, have unknown injury level, or an injury of any severity (i.e., KABCO score of K, A, B, C, O, or unknown).
- **Injury Crashes:** System-relevant crashes that involve an injury of any known severity including fatality (i.e., KABCO score of K, A, B, or C).
- **Serious Crashes:** System-relevant crashes that involve a serious or fatal injury (i.e., KABCO score of K or A).

Each nested set of system-relevant crashes is compared against the same set of control crashes, which include all injury levels (i.e., control crashes can have a KABCO score of K, A, B, C, O, or unknown). The set of control crashes remains constant because it is simply meant to represent general exposure. Related, it would not be appropriate to compare serious crashes of unequipped vehicles to serious crashes of equipped vehicles because, in cases with equipped vehicles, some crashes that would have been serious crashes would have been either mitigated (become minor or no-injury crashes) or completely prevented.



Code	Definition
K	Fatal Injury
A	Suspected Serious Injury
B	Suspected Minor Injury
C	Possible Injury
O	No Apparent Injury

Figure 2-3 Nested Injury Structure

For each set of ADAS features in this study, PARTS fit separate logistic regression models for each of the three nested system-relevant injury sets (All Crashes, Injury Crashes, and Serious Crashes) along with the full set of control crashes for all three.

2.3 Related Work

In preparation for conducting this study, PARTS conducted a literature review (see Appendix A). This review focused on recent studies (approximately in the past 5 years) that had comparable questions about real-world ADAS effectiveness and a large volume of data linking vehicle equipage to crashes. Many experts have contributed to the field of traffic safety upon which this study builds. Respected organizations have addressed aspects of ADAS performance, though not necessarily with the scope, sample size, or approach that this PARTS study did. For example, researchers with the University of Michigan Transportation Research Institute (UMTRI) [6] [7] [8] [9] and Impact Research/Toyota [10] [11] have studied the effectiveness of ADAS features but have done so for only a single automobile manufacturer and a more limited sample size. Researchers with the Insurance Institute for Highway Safety (IIHS) [12] [13] [14] have looked at effectiveness of ADAS features across a variety of automobile manufactures but with smaller sample sizes.

Through its literature review and consultation with principal investigators at UMTRI, PARTS decided to adopt methods that were similar to those used by UMTRI in related studies of ADAS. For example, like UMTRI, PARTS also linked similar states' crash data to a broader set of vehicles, used the method of quasi-induced exposure via a logistic regression, controlled for similar covariates, and made decisions about which covariates to include in logistic regression based on Bayesian Information Criterion (BIC). Other studies in the literature review were broadly consistent with this approach.

3 Data and Methodology

3.1 Data Overview

This section provides an overview of the nature and scope of data sources used for this PARTS study and how MITRE merged the data sources in preparation for analysis.

This PARTS study used two primary data sources:

1. **Vehicle data.** OEM-provided data on vehicles for select makes/models for 2015–2020 model years, at the Vehicle Identification Number (VIN) level.
2. **Crash data.** NHTSA-provided 2016–2021 police-reported crash data for select states, at the 17-digit VIN level.

3.1.1 Vehicle Data

Vehicle data includes the ADAS features on each vehicle, build date, sold or customer delivery date, sales market (used to filter U.S.-only car market), and sale type (retail or fleet). This study's results are based on data from the following industry partners:

- American Honda Motor Co., Inc. – includes the Honda and Acura brands
- General Motors LLC – includes the Buick, Cadillac, Chevrolet, and GMC brands
- Mazda North American Operations
- Mitsubishi Motors R&D of America, Inc.
- Nissan North America, Inc.
- Stellantis (FCA US LLC) – includes the Alfa Romeo, Chrysler, Dodge, Fiat, Jeep, and Ram brands
- Subaru Corporation
- Toyota Motor North America, Inc. – includes the Toyota and Lexus brands

The data included 93 models from model years 2015–2020 and covered seven vehicle segments, as shown in Figure 3-1: Small Car, Midsize Car, Large Car, Small Sport Utility Vehicle (SUV), Midsize SUV, Pick-Up & Large SUV, and Minivan. PARTS determined these vehicle segments based on the IIHS-Highway Loss Data Institute (HLDI) vehicle segment definitions with the following modifications: consolidated into fewer segments to ensure at least 3 models within a segment; assigned model twins to the same segment when vehicle specifications were sufficiently similar based on OEM input about vehicle mass, structure, or other commonalities; and adjusted mid-size SUV criteria with the effect of moving some 3-row SUVs from the small SUV to the midsize SUV segment [15].

	OEM								
	GM	HONDA	MAZDA	MITSUBISHI	NISSAN	STELLANTIS	SUBARU	TOYOTA	Total
Small Car		Acura ILX Honda Civic, Fit, & Insight	Mazda3 sedan & hatchback		Versa Sentra		Impreza WRX Crosstrek	Toyota Corolla, Prius, & C-HR	14
Midsize Car	Buick Regal Chevrolet Malibu	Acura TLX Honda Accord	Mazda6		Altima Maxima	Alfa Romeo Giulia Chrysler 200	Legacy Outback	Toyota Camry Lexus IS	13
Large Car	Buick LaCrosse Chevrolet Impala					Chrysler 300 Dodge Charger & Challenger		Toyota Avalon Lexus ES & LS	8
Small SUV	Buick Envision Chevrolet Equinox GMC Terrain	Acura RDX Honda HR-V & CR-V	CX-3 CX-5 CX-30	Outlander Sport Eclipse Cross	Rogue	Fiat 500X Jeep Renegade, Compass, & Wrangler 2DR	Forester	Toyota RAV4 Lexus NX	19
Midsize SUV	Buick Enclave Chevrolet Traverse Cadillac SRX & XT5 GMC Acadia	Acura MDX Honda Pilot & Passport	CX-9	Outlander	Murano Pathfinder	Alfa Romeo Stelvio Dodge Durango Jeep Cherokee, Grand Cherokee, & Wrangler Unlimited	Ascent	Toyota Highlander & 4Runner Lexus RX & GX	22
Pick-Up and Large SUV	Chevrolet Tahoe / GMC Yukon GMC Sierra 1500	Honda Ridgeline			Armada Titan Frontier	Jeep Gladiator Ram 1500 Ram 2500 Ram 3500		Toyota Tundra, Tacoma, & Sequoia	14
Minivan		Honda Odyssey				Chrysler Pacifica		Toyota Sienna	3

Figure 3-1 Vehicle Data: Mapping Models to Segments

PARTS selected the models in Figure 3-1 based on the following guidelines:

- **Sufficient sample size.** A minimum of approximately 5,000 model sales per year, which helped ensure a sufficient sample size for analysis and reduced the costs of data ingest and processing.
- **ADAS features.** At least one model year for each model was required to have at least one ADAS feature in scope for the analysis.
- **Non-attribution.** Among other data protection measures, PARTS required data from at least 3 OEMs to be included to produce a given analytic result, which excluded some models.

3.1.2 Crash Data

This study used crash data from 13 states provided by NHTSA through its Consolidated State Crash (CSC) database, which consolidates police-reported crashes received from states through the new Electronic Data Transfer (EDT) process. The data used is a census of all police-reported crashes in those states. It is limited by the information available in the original state-level crash report. Specific fields and data elements available for the crashes vary by state.

This study uses crashes that occurred between January 2016 and August 2021 for the 13 states included in the analysis (see Table 3-1). While other states were available in the EDT-driven CSC data, PARTS did not include them because they did not contain a historical archive within the study date range or were missing critical fields necessary for analysis.[4]

Table 3-1 Crash Data by State and Time Period Covered

State (Acronym)	Start Date	End Date
Arkansas (AR)	1/1/2016	8/2/2021
Connecticut (CT)	1/1/2016	7/30/2021
Florida (FL)	1/1/2016	8/1/2021
Indiana (IN)	1/1/2016	7/28/2021
Iowa (IA)	1/1/2017*	8/1/2021
Maryland (MD)	1/1/2016	8/3/2021
Nevada (NV)	1/2/2018*	8/3/2021

State (Acronym)	Start Date	End Date
Ohio (OH)	1/1/2019*	7/31/2021
Tennessee (TN)	1/1/2018*	8/1/2021
Texas (TX)	1/1/2018*	8/2/2021
Utah (UT)	1/1/2017*	8/2/2021
Virginia (VA)	1/1/2016	8/2/2021
Wisconsin (WI)	1/1/2018*	8/2/2021

** Asterisk and blue text indicate meaningfully different start dates*

There are some limitations of police-reported crash reports. KABCO [5], the framework for categorizing injury information used within the crash database, may not reflect precisely the injuries, injury type, or body region compared against the Abbreviation Injury Scale [16] [17] [18] [19]. Some information documented in the crash report is subjective by the police officer

[4] States with available crash data that PARTS considered and ultimately decided not to use are California, Illinois, Kansas, Maine, Nebraska, and Washington.

and may be reported inconsistently between officers and states (e.g., driver distraction at time of crash). Crash reports may have limited or no information on relevant factors (e.g., actual speed of the vehicle, road infrastructure that may impact the effectiveness of these systems). These limitations with police-reported crash data are known and generally accepted by this and other related studies, and do not present an outsize concern regarding the results.

3.1.3 Descriptive Statistics of the Study Dataset

This section includes high-level descriptive statistics to highlight some important characteristics of the joined study dataset. The descriptive statistics below show vehicle counts by the year the crash occurred (Crash Year), the model year of the vehicle involved in the crash (Model Year), the state where the crash occurred (Crash State), and the segment of vehicle involved in the crash (Vehicle Segment).

3.1.3.1 Crash Vehicles by Crash Year

The count of crash vehicles by crash year, for any type of crash, increases from 2016 to 2019 and then decreases from 2020 to 2021 (see Figure 3-2). There are several factors that cause this pattern. First, as the crash years become more recent, there are more vehicle models that have matching VINs in the study dataset, causing an increasing trend. Early crash years cannot have matching VINs for vehicle models not yet introduced (e.g., crash year 2016 can only have VINs matching model years 2015 and 2016), while later crash years can have matching VINs for early and later model years. Secondly, some states (e.g., Iowa, Ohio, Tennessee, Texas, Utah, Wisconsin) did not have crash data records for early crash years. The decrease in 2021 is due to the partial reporting year through August. Additionally, the impact of COVID-19 in crash years 2020 and 2021 decreased the number of vehicles on the roads [20].

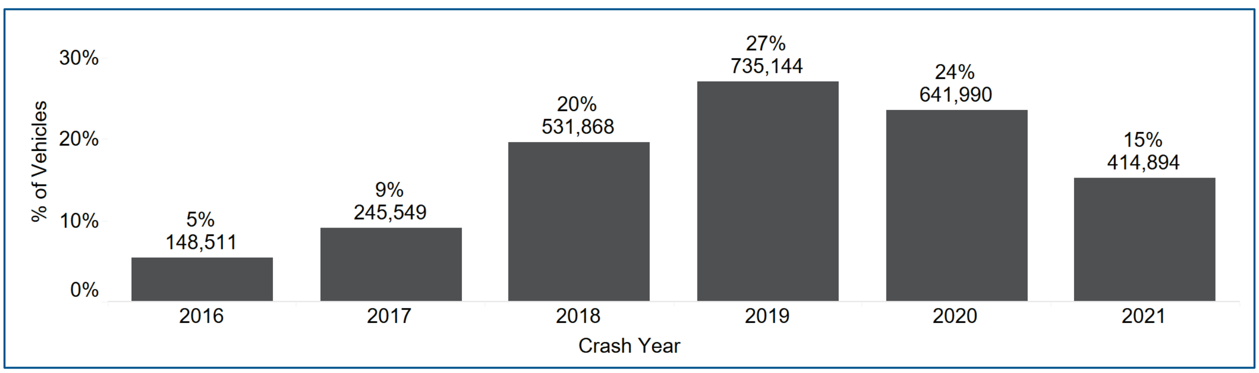


Figure 3-2 Crash Vehicle Counts by Crash Year

3.1.3.2 Crash Vehicles by Model Year

The count of crash vehicles by vehicle model year, for any type of crash, decreases, as shown in Figure 3-3. The decrease is due to the matching between model year and crash year. Early model years can be observed in all crash years in the study, while later model years can be observed only in later crash years.

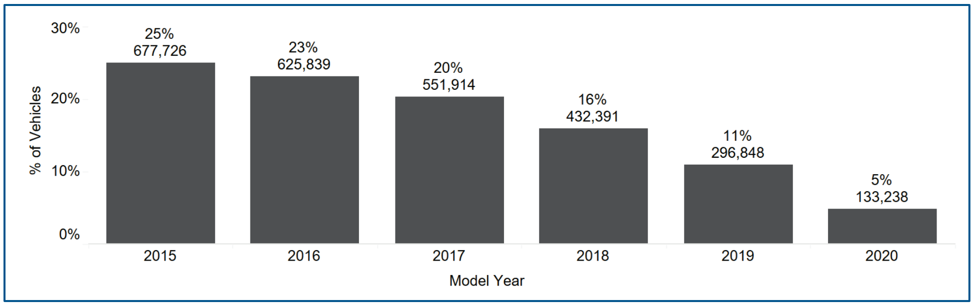


Figure 3-3 Crash Vehicle Counts by Model Year

3.1.3.3 Crash Vehicles by State

The count of vehicles by state, for any type of crash, shows that the proportion of crashes contributed by each state varies (see Figure 3-4). Florida contributes the largest number of crashes, which is a substantial portion of all crashes, followed by Texas. The variability is likely partly due to a larger population of vehicles and drivers in Florida and Texas as compared to other states in the study. Differences can also be due to state-level differences in reporting practices, roadway environments, and population demographics (e.g., income, education, and other attributes could impact the proportion of people purchasing vehicles with ADAS features). As noted in Section 3.1.2 above, some states do not have crash records for the early part of the study period, which deflates the number of crashes that a state is contributing.

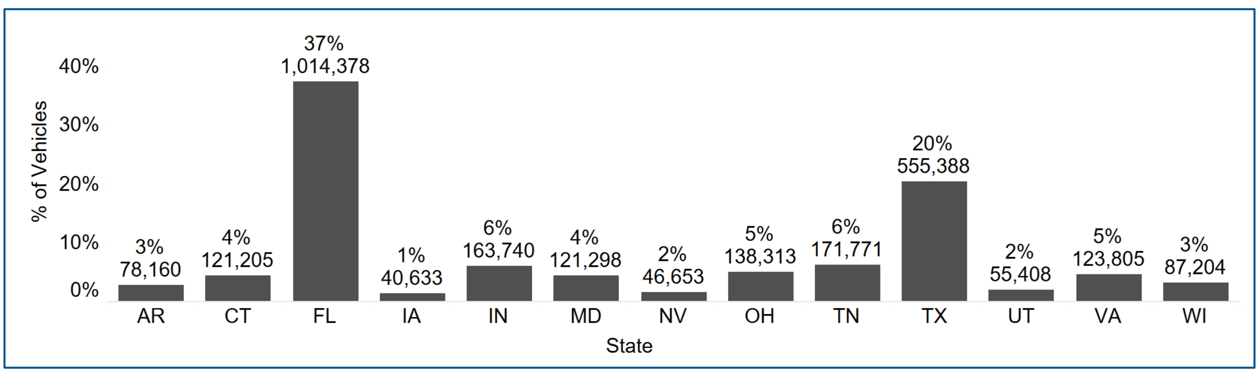


Figure 3-4 Crash Vehicle Counts by State

3.1.3.4 Crash Vehicles by Vehicle Segment

The count of crash vehicles by vehicle segment, for all crashes (see Figure 3-5), highlights that vehicle segments contribute different proportions to the study dataset. The difference in crashes by vehicle segment may be due to the specific models each OEM selected for contribution to this study, the relative market share of each segment given buying preferences among U.S. consumers, and a variety of other factors.

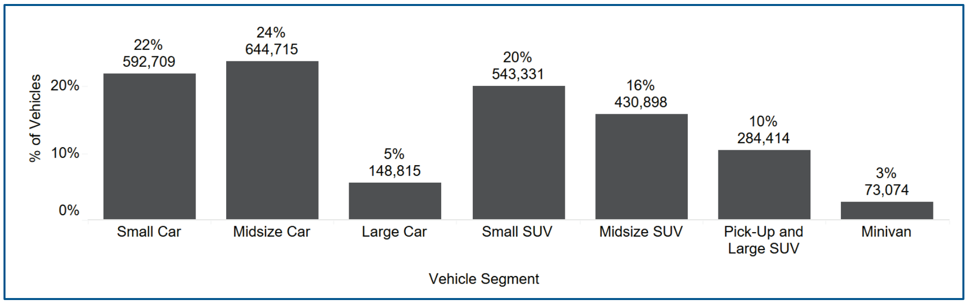


Figure 3-5 Crash Vehicle Counts by Vehicle Segment

3.2 Methodology Overview

This study used quasi-induced exposure – comparing vehicles equipped with the set of ADAS features under study against vehicles without those features – and logistic regression to estimate the reduction in system-relevant crashes due to the presence of vehicles equipped with ADAS.

3.2.1 Crash Type Definitions

To assess ADAS feature effectiveness in reducing crashes using the quasi-induced exposure method requires that PARTS maps crashes that are relevant to that feature as well as crashes comprising the control group (i.e., indicating exposure). For each crash type, MITRE used this crash mapping to prepare data for the logistic regression model. Note that MITRE included vehicles involved in multiple separate crashes (e.g., a non-motorist crash and a different, front-to-rear crash) in the prepared datasets for each of those crash types.

3.2.1.1 Control Crashes

PARTS defined the control group for analysis of all ADAS features as participating OEM vehicles that were the struck vehicles in front-to-rear collisions. This control group provided the indication of vehicle exposure in the quasi-induced exposure method noted above. PARTS identified these vehicles using all of the following selection criteria (logical AND):

- Manner of crash was identified as front-to-rear.
- Initial point of contact on the rear end of the vehicle.[5]
- Not a non-standard front-to-rear crash, such as vehicles that were reported to be backing up or parked (to remove these edge cases).
- Not crashes where more than two vehicles were reported (to reduce the potential for misattribution of striking and struck vehicles).

[5] Most states included in this study use clock coordinates to indicate initial point of contact for crashes (where the front center of a vehicle is 12 o'clock). PARTS considered values of 5, 6, or 7 o'clock to be rear. Some states used descriptions such as "rear," "right rear bumper," and "rear – left." PARTS mapped related phrases and clock coordinates to the construct of "rear." PARTS used a similar mapping technique to harmonize the construct of "front" given varied state crash data.

This control group definition is consistent with multiple studies and is an accepted practice for identifying exposure to collisions.

This study also investigated an alternative control group defined as vehicles in angled collisions at intersections; PARTS did not expect ADAS features to affect the frequency of such collisions. PARTS used this alternative control crash in a sensitivity analysis of the system effectiveness results (see Appendix B).

3.2.1.2 Front-to-rear Crashes (FCW/AEB System-relevant)

PARTS defined the system-relevant crashes for FCW and AEB as participating OEM vehicles that were the striking vehicle in front-to-rear collisions. PARTS identified these vehicles using all of the following selection criteria (logical AND):

- Manner of crash was identified as front-to-rear.
- Initial point of contact was on the front end of the vehicle.
- Not a non-standard front-to-rear crash, such as vehicles that were reported to be backing up or parked (to remove these non-system-relevant cases).
- Not crashes where more than two vehicles were reported (to reduce the potential for misattribution of striking and struck vehicles).

3.2.1.3 Frontal Crashes with a Non-motorist (PAEB System-relevant)

PARTS defined the system-relevant crashes for PAEB as participating OEM vehicles that were the striking vehicle in a pedestrian or other non-motorist crash. PARTS identified these vehicles using all of the following selection criteria (logical AND):

- Manner of crash was identified as involving at least one pedestrian or non-motorist.
- Initial point of contact was on the front end of the vehicle.
- First event reported was a pedestrian or non-motorist (e.g., persons on bicycles, scooters, wheelchairs).
- Not a non-standard front-to-rear crash, such as vehicles that were reported to be backing up or parked (to remove these non-system-relevant cases).
- Not crashes where more than one vehicle was reported (to ensure the collision occurred between the vehicle and the pedestrian and that the pedestrian was not impacted after another vehicle was struck).

This mapping did not address specific pedestrian actions such as walking alongside or crossing the road, or whether the pedestrian was obscured from the driver or vehicle prior to collision, given that this data was not readily available and was not a focus of this study. The operational design of some PAEB systems may not address some specific types of pedestrians and non-motorists, or some specific actions they may take. This mapping also included non-motorists in the same sample as pedestrians; however, these groups may be addressed differently by the equipped PAEB systems.

3.2.1.4 Single-vehicle Road-departure Crashes (LKA/LDW/LCA System-relevant)

PARTS defined the system-relevant crash for lateral ADAS systems (LKA, LDW, and LCA) as participating OEM vehicles that were in single-vehicle road-departure collisions. PARTS identified these vehicles using all of the following selection criteria (logical AND):

- Crashes where exactly one vehicle was reported.
- First event reported was ran off the road, cross centerline, cross median, collision with fixed objects, or rollover.
- Vehicle maneuver at the time of crash was either: going straight, negotiating a curve, leaving traffic lane, or ran off road.

Note that PARTS also considered sideswipe same-direction and opposite-direction crashes to be system-relevant for lateral ADAS features but did not include them here due to data limitations. Specifically, the crash data did not, with certainty, identify the vehicle that left its lane. As a result, both vehicles in a sideswipe collision would be included in the system-relevant set. This is an issue because it does not allow the study to isolate the vehicle where the ADAS feature was truly relevant. Therefore, PARTS focused on single-vehicle road-departure crashes as providing more reliable effectiveness estimates. Sideswipe same-direction and opposite-direction crash definitions and effectiveness estimates are presented in Appendix C.

3.2.2 Preparing and Linking Data Sources

MITRE processed vehicle data for this study to harmonize vehicles by segment, as well as to map OEM-specific terms for specific ADAS features to standard definitions of the six features under study. This data processing represented a substantial and collaborative effort among PARTS partners, resulting in a uniquely robust and consistent dataset about ADAS equipage and model segmentation.

MITRE also worked closely with PARTS partners to harmonize crash data to mitigate inconsistencies across states. NHTSA worked to standardize a number of fields in the crash data it provided, such as the highest injury level and whether alcohol or drugs were involved. MITRE processed the crash data to standardize/reclassify additional fields needed for this analysis, such as the first vehicle event in the sequence of events, environmental conditions, and collision point of contact. PARTS also recognized that states have different crash reporting practices, some of which cannot be fully accounted for in the analysis, such as when a field (e.g., rural/urban) was not available for certain states, or when state definitions vary for the same field (e.g., the definition of driver impaired in one state may be illegal drug/alcohol intoxication, while another state may include both illegal and prescription drug use, alcohol use, and drowsiness; the dollar threshold triggering property damage crashes varies). Notwithstanding these caveats, the efforts of MITRE and the PARTS partners to harmonize crash data resulted in a large-scale and sufficiently consistent dataset that was sufficiently robust for this analysis.

MITRE prepared the crash data and vehicle data for analysis by using VINs to join the datasets. The study included crashes that had at least one participating OEM vehicle in the analysis. The joined data resulted in a total of 2.4 million crash-involved vehicles and 2.7 million crashes. This statistic separately counts vehicles that are involved in multiple crashes at different times, and multiple vehicles that are in the same crash. MITRE safeguarded the pooled data from view by any partner and conducted analysis so that results are not attributed to any OEM (see Figure 3-6).

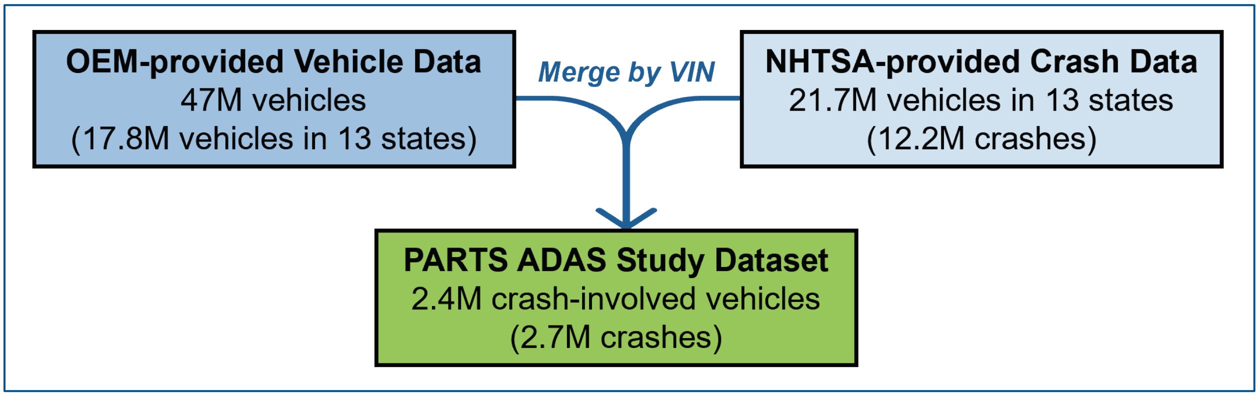


Figure 3-6 Joining Crash Data and Vehicle Data

3.2.2.1 Missing Data

PARTS deleted observations from the study dataset if they were missing any of the variables expected for the logistic regression (see Section 3.2.2). These deleted observations represented about 10% of the data. The sample sizes shown in Chapter 5 are those that this study included in the logistic regression (i.e., exclusive of deleted observations).

3.2.3 Quasi-induced Exposure

This PARTS study measured the effectiveness of each ADAS feature (or combination of ADAS features) with respect to reducing a relevant crash type. The PARTS study dataset lacked a reliable traditional exposure measure (e.g., vehicle miles traveled) and therefore relied on the quasi-induced exposure method. Quasi-induced exposure uses control (i.e., exposure) crashes within the crash dataset to gain insights into exposure. These control crashes should be unaffected by the ADAS feature being studied and occur at a similar rate in both equipped and unequipped populations [8]. The effectiveness of the ADAS feature is determined by looking at the rate of system-relevant crashes to the control crash (referred to as odds) comparing equipped to unequipped vehicles. For the simplest case, when the ADAS feature is effectively reducing crashes, the rate of system-relevant to control crashes is lower for equipped compared to unequipped vehicles. Please see Appendix D for an illustration of quasi-induced exposure.

This method of quasi-induced exposure has been widely used when studying ADAS feature effectiveness. IIHS [21], Impact Research/Toyota [10], and UMTRI [9] (which has a particularly accessible explanation of quasi-induced exposure) have all used quasi-induced exposure to study ADAS feature effectiveness.

3.2.4 Logistic Regression Model Design

PARTS used logistic regression to estimate the effectiveness of sets of ADAS features in reducing relevant crashes (see Section 3.2) while controlling for several key factors (or covariates) that could affect the ADAS effectiveness estimate. Logistic regression provides a convenient way to incorporate factors that could potentially affect the rate of crashes (e.g., driver age, driver gender, weather) while maintaining enough statistical power to detect an effect (e.g., crash reduction due to ADAS feature).

The general logistic regression equation is similar to a linear regression, but occurs with regard to the log-odds for a binary outcome variable:

$$Log(odds) = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \dots. + \beta_D * x_D$$

The binary outcome variable (i.e., $Log(odds)$) is on the left side of the equation. The explanatory variables (on the right side of the equation) are $x_1, x_2, \dots., x_D$ and are assumed to follow a linear relationship ($\beta_1, \beta_2, \dots, \beta_d$) with respect to the $Log(odds)$.[6]

PARTS set the binary outcome variable as system-relevant crashes (coded as 1) and control crashes (coded as 0). PARTS included sets of ADAS features as an explanatory variable (e.g., x_1) to enable estimates of effectiveness. PARTS coded ADAS features as binary variables such that the associated coefficient (β_1) represents the log-odds difference between equipped and unequipped vehicles, which is the log of the odds ratio. Exponentiating the ADAS feature coefficient (β_1) yields the odds ratio of equipped to unequipped:

$$Odds\ Ratio = e^{\beta_1}$$

To measure the uncertainty of the estimates, PARTS calculated Wald confidence intervals (CIs) at the alpha = 0.05 level for the coefficients. Again, the CI calculations take place in log space but were transformed to Odds Ratio for interpretability. To formulate ADAS effectiveness more intuitively, where a higher value indicates more effectiveness, PARTS calculated the percentage reduction of equipped odds compared to unequipped odds as follows:

$$Effectiveness = Percentage \quad = (1 - e^{\beta_1}) * 100$$

The described calculations result in effectiveness weighted across the OEMs, vehicle models, environmental conditions, and driver populations as they appear in the dataset. Along with sets of ADAS features, PARTS included several covariates in the logistic regression to control for their influence on crash outcome, and thus on effectiveness (if not accounted for, those factors' influence could bias the estimate of effectiveness).

3.2.4.1 Covariate Definitions

This section describes the driver, vehicle, environmental, and crash-related covariates PARTS identified for the logistic regression models (see Table 3-2).

[6] Note that this assumption of linearity is less of a concern for this study given PARTS transformed continuous variables into categorical variables, which effectively allows for non-linear relationships. For example, PARTS coded driver age as categorical age groups, thus allowing the relationship between the log-odds and driver age to have a U-shaped relationship (i.e., both younger and older drivers tending to get in more system-relevant crashes). The practice of transforming covariates into categorical groups is aligned with many studies' literature [9] [11] [14].

Table 3-2 Logistic Regression Model Covariates

Variable	Explanation	Specification in Logistic Regression	Additional Notes
Driver Age	Driver age as reported in CSC	14–24, 25–34, 35–54, 55–64, 65–74, 75+	Set to *None* if age <14 or >115.
Driver Alcohol/ Drugs	Drug or alcohol use attributed to driver in CSC	Boolean – True if either drugs or alcohol reported	Not always marked and different from state to state. *Not a number (nan)* and *unknown* set to False due to some states note only when alcohol present.
Driver Distracted	If driver was reported as being distracted in CSC	Boolean – True if driver distracted reported	Not always marked and different from state to state. *Nan, unknown*, and *NOT DISTRACTED* set to False.
Driver Gender	Reported in CSC	Female, Male	Limited number of entries were *unknown*, *nan*, etc. Such entries were removed.
Vehicle Model	Each individual vehicle model	See Section 3.1.1	Likely correlated with specific driver behavior, which is not perfectly represented in the logistic regression
Vehicle Model Year	MY of vehicle manufacture	2015, …, 2020	Limited to model years 2015 through 2020
Vehicle Sales Type	If vehicle was fleet or retail at time of sale	Fleet, Retail	At time of initial sale, but do not know if vehicle was still a fleet vehicle at time of crash
Weather	If atmospheric conditions were *clear* or *overcast*, from CSC reporting	Boolean – True if weather was bad	*Not Reported*, *Reported as Unknown*, and *Unknown* were removed. Various other values were *precipitation; frozen precipitation; fog or smoke; blowing sand, soil, or snow; strong wind…*
Road Surface	Was road dry or not dry at time of crash, from CSC reporting	Boolean – True if road was not dry	*Not Reported*, *Reported as Unknown*, and *Unknown* were removed. Various other values were *wet, snow/slush, ice/frost, mud/dirt/sand/gravel…*
Light Condition	Light condition from CSC reporting	Daylight, Dark, Dawn/Dusk	*Unknown* and *nan* were ignored.
Road Alignment	Reported road alignment in CSC	Straight, Curve	Only if curved or straight not amount of curve. *Unknown*, *other*, *nan* were removed.
Intersection	Whether the crash occurred at a roadway intersection	Boolean – True if crash marked as occurring at an intersection	*Intersection* set to True, all else set to False.
Crash State	State where crash occurred	AR, CT, FL, …	
Crash Year	Year in which crash occurred	2016, 2017, 2018, 2019, 2020, 2021	
Crash Posted Speed Limit	Reported speed limit of roadway where crash occurred, in miles per hour	Under 25, 25–34, 35–44, 45–54, 55–64, 65 or over	Posted speed limit, not actual speed of vehicle

3.2.4.2 Covariates as Main Effects

PARTS selected the above set of covariates as main effect candidates within the logistic regression models.[7] PARTS selected the list of potential covariates through:

1. Surveying literature on past research to identify factors previously important to control for in ADAS effectiveness.
2. Conducting discussions with partners to identify other potential factors that could affect the performance of ADAS.

PARTS included candidate covariates as main effects in a logistic regression model for front-to-rear crashes, the crash category containing the largest number of crashes. PARTS conducted a BIC backward selection process to determine which candidate covariates should remain in the model. BIC favors less complex (more conservative) models than other commonly used methods (e.g., Akaike Information Criteria and Likelihood Ratio Test at the $\alpha = 0.05$ level). PARTS then made various revisions (e.g., more precisely dividing the covariate, which effectively adds categories) to construct categorical variables, such as driver age and speed limit, to fine-tune the enumerated categories.

The set of covariates above were selected for inclusion by BIC (i.e., BIC was lower with the covariate included) for front-to-rear crashes and were included as main effects in the logistic regression model. Given the conservative nature of BIC in adding parameters (whether as main effects or interactions), a factor being identified by BIC is a strong indication that that factor should be controlled for when studying ADAS feature effectiveness.

Of note is that BIC selected crash year for inclusion. The odds ratio, regardless of equipage, showed a general upward trend with respect to crash year. The causes of the upward trend with crash year could be several factors, with one logical explanation being that control crashes decrease in later years due to the increasing prevalence of AEB-equipped vehicles on the road. Inclusion of crash year as a main effect allows us to appropriately control for this influence.

PARTS generally included covariates as main effects. This helps control for these factors in influencing ADAS feature effectiveness estimates [22]. PARTS adopted the following approach to strengthen confidence in the logistic regression results:

1. Including factors selected for all front-to-rear crashes in the logistic regression for injury front-to-rear crashes and serious front-to-rear crashes.
2. Including factors selected for all front-to-rear crashes in the logistic regression models for single-vehicle road-departure and non-motorist crashes (including all, injury, and serious crashes) based on the assumption that the factors were likely to be important for other crash types.

[7] Note that PARTS did not include vehicle segment as a main effect because vehicle model provides that information. However, PARTS information protections do not allow reporting results by individual vehicle model. PARTS tested for interaction effects to the vehicle segment level.

By including the same covariates across the logistic regressions, researchers minimized the likelihood of this study missing an important factor to control for, due to limited statistical power driven by the smaller sample sizes associated with the single-vehicle road-departure and non-motorist crash datasets.

In addition to the covariates listed above, this study included blind spot warning (BSW) as a main effect for sideswipe same-direction crashes. PARTS included BSW not to estimate its effectiveness but rather to control for BSW influence while estimating effectiveness for LDW, LKA, and LCA. The study did not account for the presence of other ADAS features.

3.2.4.3 Covariates as Interactions

PARTS also sought to examine whether ADAS feature effectiveness changed for different conditions or populations. To find where effectiveness changes may be present with respect to a factor, this study included the covariates in the logistic regression model as an interaction with the ADAS features on an individual basis, with all covariates as main effects. This study used BIC to determine if each interaction was contributing meaningful information to the logistic regression model (i.e., BIC was lower with the interaction included). If BIC identified an interaction as adding meaningful information, then PARTS interpreted that as an indication that ADAS effectiveness is changing with respect to that covariate (see Appendix E for interaction estimates and CIs). PARTS applied a Bonferroni correction to the CIs to control for false positive rate by covariate (i.e., divided the false positive error by the number of levels for the covariate).

Changes in effectiveness by covariates could be partially or solely due to confounding factors. This is true even for covariates within the logistic regression specification because the interactions were tested individually. Confounding factors can be particularly problematic for covariates related to time. For example, model year is confounded by crash year, years in use, equipage of vehicle models, and other changes to the population.

Related, if the logistic regression is not specified correctly (e.g., it is missing important factors), then the ADAS feature effectiveness estimates could be biased due to the influence of those factors. As a part of the process of analytic discovery, PARTS ran model iterations with and without some of the covariates noted above. This resulted in differences in estimated effectiveness that in some cases were large in magnitude, particularly for single-vehicle road-departure and non-motorist crashes. Examples include finding that excluding vehicle model or excluding crash year had large impacts on the effectiveness estimates for single-vehicle road-departure and non-motorist crashes. The single-vehicle road-departure and non-motorist logistic regression models are more sensitive to uncertainty based on misspecification than the front-to-rear models. PARTS presents the effectiveness estimates and their uncertainty assuming the correct specification.

4 Results

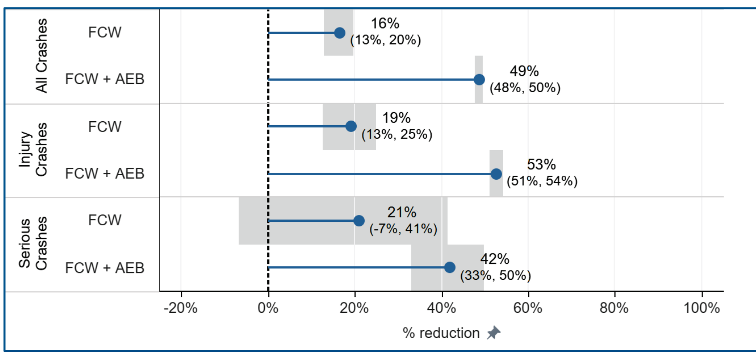
This chapter presents results for the PARTS analysis of the effectiveness of three groupings of ADAS features in avoiding system-relevant crashes – FCW/AEB for front-to-rear crashes, PAEB for frontal crashes with non-motorists, and LDW/LKA/LCA for single-vehicle road-departure crashes. Model fit statistics are presented in Appendix F and interaction effects in Appendix D.

4.1 FCW/AEB Reduction in Front-to-rear Crashes

This section highlights results from the PARTS analysis of front-to-rear crashes when the striking vehicle is equipped with FCW or FCW + AEB compared to vehicles not equipped with either, for all front-to-rear crashes, injury front-to-rear crashes, and serious front-to-rear crashes.

4.1.1 FCW/AEB Results Summary

Broadly, PARTS partners' hypothesis that FCW and AEB are effective in reducing crashes was borne out by the study findings.[8] In particular, vehicles equipped with FCW + AEB showed a substantial crash reduction of about half across crash types, as shown in Figure 4-1 (associated sample sizes are shown in the data table to the right of the chart).[9]



		System Relevant	Control
All Crashes	Neither	171,409	251,957
	FCW	5,769	12,893
	FCW + AEB	39,297	137,157
Injury Crashes	Neither	41,440	251,957
	FCW	1,289	12,893
	FCW + AEB	8,598	137,157
Serious Crashes	Neither	1,918	251,957
	FCW	67	12,893
	FCW + AEB	440	137,157

Figure 4-1 Results for FCW/AEB and Associated Sample Sizes

4.1.2 FCW/AEB Results for All Crashes

As shown in Figure 4-1, FCW + AEB had an estimated reduction of 49% (48 to 50%) in all front-to-rear crashes compared against vehicles not equipped with FCW or AEB. FCW had an estimated reduction of 16% (13 to 20%) compared against vehicles not equipped with FCW or AEB. These estimated crash reductions of FCW and FCW + AEB are in line with past research

[8] By convention, this study reports the 95% confidence interval (CI) in parentheses for point estimates. The CI indicates how much uncertainty is around that estimate based on this study. This study calculated the CI with Wald at $\alpha = 0.05$. The wider the CI, the more uncertainty there is that a reported reduction in crashes would be replicated in future studies.

[9] By convention, gray text in data tables indicates a result that is not necessarily different from zero based on the CI including zero. The uncertainty that is indicated when CIs include zero could be thought of as similar to when traditional hypothesis testing yields a result that is not significant (e.g., not statistically different from zero at the 95% confidence level).

noted in Appendix A, especially when considering the uncertainty associated with the estimates. This study found that there is a higher reduction for vehicles equipped with both FCW and AEB than vehicles equipped with FCW alone. This indicates that having an active system together with a warning is better than a warning system alone, at least for front-to-rear collisions.

4.1.3 FCW/AEB Results for Injury Crashes

PARTS additionally estimated the reduction in injury front-to-rear crashes; focusing attention on injury front-to-rear crashes resulted in a dataset that was about 20% of the total system-relevant crashes, as shown in Figure 4-1. This study estimated reductions for injury front-to-rear crashes that were slightly higher than for all crashes. FCW + AEB had an estimated reduction of 53% (51 to 54%) for injury crashes compared to vehicles not equipped with FCW or AEB. FCW had an estimated reduction of 19% (13 to 25%) for injury crashes.

4.1.4 FCW/AEB Results for Serious Crashes

PARTS estimated FCW and AEB reductions for a further subset of system-relevant crashes – only those where any participant suffered a serious or fatal injury. The dataset of serious front-to-rear crashes was only about 1% of the total system-relevant crashes, as shown in Figure 4-1.

FCW + AEB had an estimated reduction of 42% (33 to 50%) for serious crashes. FCW had an estimated reduction of 21% (-7 to 41%) for serious crashes. Due to the much more limited sample sizes of serious crashes, the uncertainty in the estimate is much larger. In fact, the FCW case resulted in a CI that covered zero reduction in crashes (i.e., may not necessarily be effective).

4.1.5 FCW/AEB Results by Condition

For the all front-to-rear crashes model, this study had eight interactions of FCW + AEB with covariates identified by BIC (driver age, weather, road surface, light, roadway alignment, intersection, speed limit, and sales type), while FCW did not have any interactions with a covariate identified by BIC.

This study also found that the crash reduction effectiveness of FCW + AEB changes with respect to several conditions; its effectiveness was:

- Lower for dark at 42% (39 to 44%) and dawn/dusk at 44% (38 to 48%) light conditions than for daylight at 50% (49 to 52%).
- Lower for speed limits under 35 mph than 35 mph and above, with speed limits 25–34 at 44% (42 to 47%) and speed limits under 25 mph at 24% (16 to 32%).
- Lower as driver age increased, with effectiveness for age 55–64 at 44% (41 to 46%), age 65–74 at 42% (39 to 45%), and age 75 and older at 34% (29 to 38%).
- Lower for wet roads at 44% (42 to 47%) and bad weather at 42% (39 to 45%) than dry roads at 49% (48 to 51%) and good weather at 49% (48 to 51%).

- Lower for fleet vehicles at 43% (40 to 45%) than retail vehicles at 50% (48 to 51%). Note this categorization of fleet vs. retail is based on time of sale.
- Lower for crashes occurring at an intersection at 45% (43 to 46%), and lower for crashes occurring on curved road segments at 34% (30 to 38%) than straight road segments at 50% (49 to 51%).

In the injury front-to-rear crashes model, FCW + AEB had interactions with five covariates identified by BIC (weather, road surface, light condition, roadway alignment, sales type), while FCW did not have any interactions with a covariate identified by BIC. The overall trends for injury FCW + AEB interactions with covariates (see Appendix E) were similar to the interactions noted above for the all front-to-rear crashes model.

In the serious front-to-rear crashes model, no interactions were identified by BIC for FCW + AEB or FCW.

PARTS estimated reductions for the ADAS features using an alternative control crash to test whether the reductions were sensitive to the choice of control crashes; the reductions for the alternate control are presented in Appendix B. Generally, the reduction PARTS estimated using the alternate control was similar to the reduction PARTS estimated using front-to-rear struck as the control crash.

The magnitude and direction of how interactions caused FCW/AEB effectiveness estimates to change generally aligned with PARTS partner expectations for many of the covariates. For more information on interaction effects, see Appendix E.

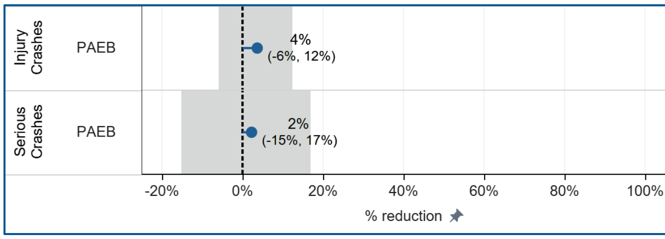
4.2 PAEB Reduction in Frontal Non-motorist Crashes

This section includes the PARTS-estimated reduction in frontal non-motorist collisions involving an injury when the striking vehicle is equipped with PAEB compared to vehicles not equipped with PAEB. Additionally, this study measured the reduction for serious non-motorist crashes. PARTS did not include an estimate of PAEB effectiveness for all crashes since this is almost the same case as injury crashes given the data.[10]

[10] The effectiveness of all crashes (i.e., both property damage and injury crashes) is not shown because over 90% of pedestrian collisions in the crash database involved an injury of some severity. This is likely due to most pedestrian-involved crashes resulting in injuries as well as reporting biases for crashes involving pedestrians. If property damage only crashes are measured together with injury crashes, then the all crashes effectiveness estimate is essentially that of crashes involving an injury because a vast majority of crashes involve an injury. Therefore, to avoid confusion of two estimates of effectiveness for crashes involving an injury, PARTS excluded the estimate including property damage only.

4.2.1 PAEB Results Summary

This PARTS study did not find a statistically significant result for PAEB effectiveness (see results and sample sizes in Figure 4-2).



		System Relevant	Control
Injury Crashes	No PAEB	5,020	286,086
	PAEB	1,271	96,417
Serious Crashes	No PAEB	1,591	285,488
	PAEB	379	95,641

Figure 4-2 Results for PAEB and Associated Sample Sizes

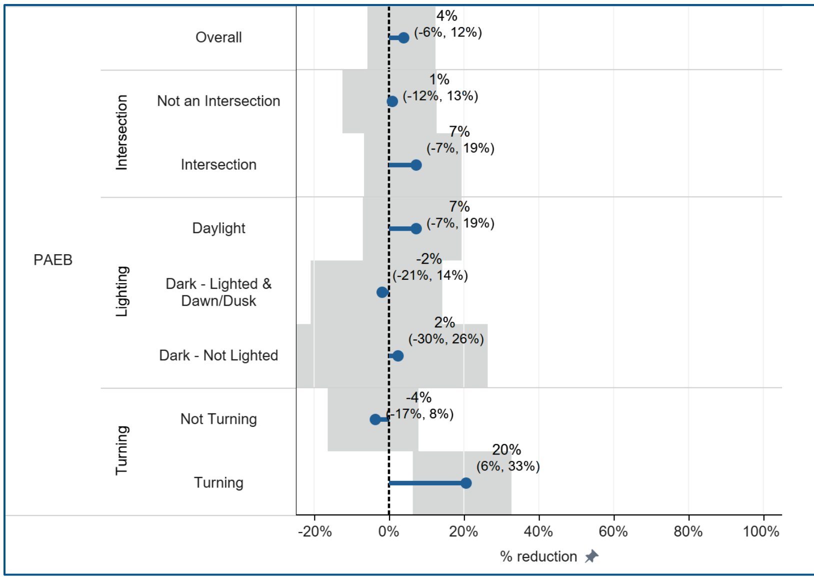
There were 1,271 injury non-motorist crashes that involved a PAEB-equipped vehicle, which is much lower than the case of FCW + AEB but similar to FCW. PARTS estimated that non-motorist collisions involving any injury severity were reduced by about 4% (-6 to 12%) when comparing vehicles equipped with PAEB against vehicles unequipped with PAEB, but the CI covering zero indicates that this is not necessarily different from zero. This study's central estimate is lower than related studies, though it still falls within the CI noted by UMTRI 2022 [9] and Impact Research/Toyota 2021 [8], and it is lower than that reported by IIHS 2022 [14]. The differences between these studies that could explain these potential differences are covered in Appendix A.

PAEB effectiveness in reducing serious non-motorist collisions (2%) was similar in magnitude, but with a wider CI (-15 to 17%) that also covered zero. This estimate aligns well with the IIHS 2022 study [14]. The 379 serious non-motorist crashes comprise about one-third of the sample size of injury non-motorist crashes, due to five vehicle models not having any system-relevant crashes. Since this study included vehicle model as a covariate, that absence of data caused instability for the estimate of the coefficients, so PARTS removed those vehicles from the regression model.

To understand the sensitivity of the estimated PAEB reductions to the definition of the control crashes, PARTS estimated the reductions using an alternate control crash type. The reductions estimated for PAEB using the alternate control crash type were very similar (see Appendix B).

4.2.2 PAEB Results of Targeted Hypothesis Testing

Given the inherent conservativism of BIC and small sample sizes, PARTS identified a set of targeted hypotheses for further testing using a less conservative approach (i.e., Wald hypothesis testing). This study identified two hypotheses, which were mimicking hypotheses tested in the IIHS [14] study (light and vehicle turning), and one hypothesis that was identified by the partners (whether crashes at intersections differed from crashes not at intersections). See results of these analyses and associated sample sizes in Figure 4-3.



			Sample Size	
			System Relevant	Control
Overall	Overall	No PAEB	5,020	286,086
		PAEB	1,271	96,417
Intersection	Not an Intersection	No PAEB	2,749	195,211
		PAEB	720	66,053
	Intersection	No PAEB	2,270	90,875
		PAEB	551	30,364
Lighting	Daylight	No PAEB	2,718	225,110
		PAEB	703	77,036
	Dark - Lighted & Dawn/Dusk	No PAEB	1,667	51,067
		PAEB	426	16,515
	Dark - Not Lighted	No PAEB	593	9,181
		PAEB	134	2,672
Turning	Not Turning	No PAEB	3,259	273,127
		PAEB	873	92,134
	Turning	No PAEB	1,761	12,595
		PAEB	398	4,283

Figure 4-3 Results for PAEB by Condition and Associated Sample Sizes

4.2.2.1 Intersection Condition

PARTS estimated the PAEB reduction for system-relevant crashes involving any injury severity by intersection condition (whether the collision occurred at an intersection or not). Prior to running this test, PARTS had no expectation as to whether PAEB would have higher or lower effectiveness for collisions at intersections. The PARTS partners deemed this covariate worthy of study because (1) collisions at intersections tend to result in lower-severity injury, (2) the speeds at intersections are different, and (3) the kinematics of non-motorists at intersections are different. PARTS found no significant difference in PAEB effectiveness for collisions occurring at an intersection compared to collisions not at intersections ($p = 0.34$); see Figure 4-3.

4.2.2.2 Lighting Condition

PARTS estimated the PAEB reductions for system-relevant crashes involving any injury severity by different light conditions. The hypothesis was that the PAEB reductions would be lower for dark not lighted conditions than conditions when some light is present (daylight or more limited light conditions of dawn/dusk or dark but lighted overhead). This study did not find a significant difference in PAEB effectiveness for dark not lighted conditions compared against daylight conditions ($p = 0.33$) or compared against more limited light conditions of dawn/dusk or dark lighted ($p = 0.63$); see Figure 4-3. IIHS 2022 [14] did see a significant difference between dark lighted conditions and the other light conditions, although the dark lighted conditions have large uncertainty (shown by width of CI), indicating a small sample size.

4.2.2.3 Vehicle Turning Condition

PARTS estimated PAEB reductions for system-relevant crashes involving any injury severity by vehicle turning condition (turning or not turning). PARTS hypothesized that PAEB effectiveness would be lower when vehicles were turning based on IIHS 2022 [14] and controlled experiments with well-defined turning scenarios.

PARTS estimated higher PAEB effectiveness when the vehicle is turning than when it is not ($p < 0.001$), which is a finding in contrast to both IIHS 2022 [14] and partners' intuition. Further investigation is needed to see if this is a true effect, due to some other confounding factor, or an artifact of the data.

The estimates above were for real-world conditions, which may differ from what is tested in controlled experiments. For example, the types of turns in real-world conditions may be different than well-defined test scenarios. Information about different types of turns (e.g., right or left turn) was not included in the analysis. Further, the turning case has very limited control crashes (only about 5% of control crashes were turns), which could influence the results. Those control crashes are also based only on the actions of the struck vehicle and not the striking vehicle, which may not align with the PAEB case. Finally, it may be that some other confounding factor is driving this difference rather than turns themselves.

One example of a possible confounding factor is speed limit. Non-motorist collisions involving a turn tend to happen more frequently at lower speed limits than collisions not involving a turn (see Figure 4-4).

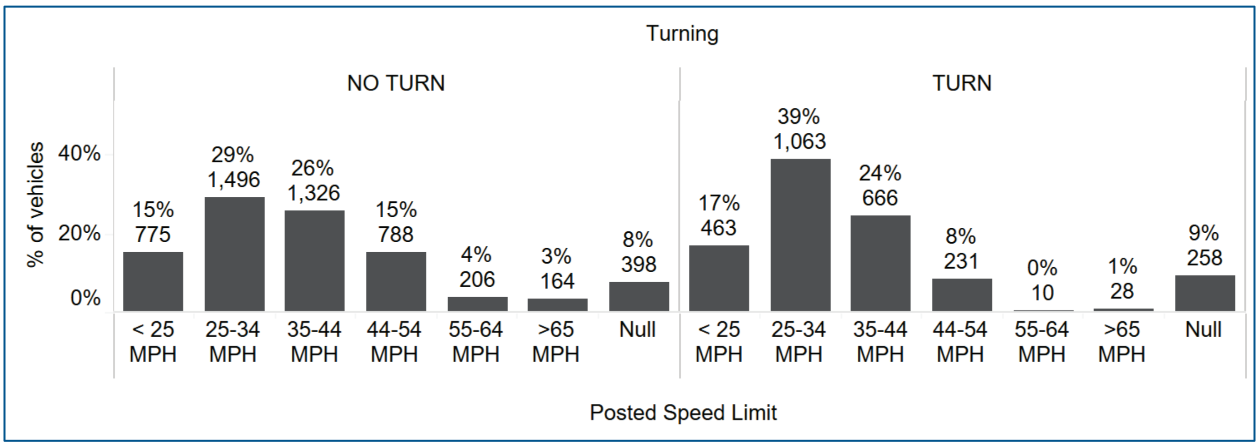


Figure 4-4 Non-motorist Crashes by Turning Condition and Speed Limit

4.2.3 PAEB Results by Condition

PARTS investigated whether PAEB effectiveness changed with respect to any of the covariates using BIC (as described above for FCW/AEB) and found that BIC did not identify any interactions. Note that there may be covariates for which changes in effectiveness exist but were not identified due to lacking power (i.e., not detecting an effect that is present) because of smaller sample sizes associated with non-motorist collisions and the conservativeness of BIC.

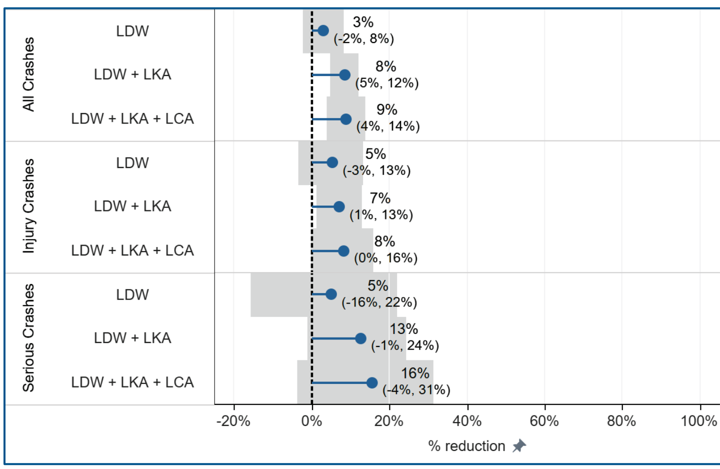
4.3 LDW/LKA/LCA Reduction in Single-vehicle Road-departure Crashes

PARTS estimated the reduction in single-vehicle road-departure crashes when the vehicle is equipped with LDW (no LKA, no LCA), equipped with LDW + LKA (no LCA), and equipped with LDW + LKA + LCA, compared against vehicles equipped with none of these lateral ADAS features. Comparing LDW + LKA and LDW + LKA + LCA against LDW provides information about the inclusion of active systems over just a warning system. When comparing LDW + LKA against LDW + LKA + LCA, the differences can be attributed to the combination of vehicles equipped with both LCA and LKA systems and the estimated effectiveness, which is confounded by usage and technical specification of both systems.

PARTS identified other system-relevant crash types for lateral ADAS, including sideswipe same-direction and opposite-direction (see Appendix C). Those crash types had limitations with respect to identifying the initiating vehicle in the crash (i.e., the vehicle leaving its lane, which lateral ADAS is intended to mitigate). Therefore, this study focused on only those crashes involving a single vehicle, specifically single-vehicle road-departure crashes.

4.3.1 LDW/LKA/LCA Results Summary

When combined with LDW, active lane keeping ADAS features (LKA and LCA) reduced the likelihood of all crashes by about a tenth, as shown in Figure 4-5, when accounting for the presence of BSW. However, study limitations did not support this finding of effectiveness in all cases of feature/crash/condition testing; further research may be required.



		System Relevant	Control
All Crashes	No Lateral ADAS Features	54,090	275,178
	LDW	3,428	22,162
	LDW + LKA	9,417	70,007
	LDW + LKA + LCA	4,300	34,660
Injury Crashes	No Lateral ADAS Features	16,324	275,178
	LDW	1,046	22,162
	LDW + LKA	2,801	70,007
	LDW + LKA + LCA	1,326	34,660
Serious Crashes	No Lateral ADAS Features	2,718	275,178
	LDW	163	22,162
	LDW + LKA	423	70,007
	LDW + LKA + LCA	197	34,660

Figure 4-5 Results for LDW/LKA/LCA and Associated Sample Sizes

4.3.2 LDW/LKA/LCA Results for All Crashes

As shown in Figure 4-5, vehicles equipped with LDW + LKA had the highest crash sample sizes. LDW and LDW + LKA + LCA had lower crash sample sizes that were similar. This study found that LDW + LKA had an estimated reduction in all single-vehicle road-departure crashes of 8% (5 to 12%) when compared against vehicles equipped with none of LDW, LKA, or LCA. Similarly, LDW + LKA + LCA had a reduction of 9% (4 to 14%) when compared against vehicles equipped with none of LDW, LKA, or LCA. Both preceding active lane management ADAS feature sets had similar crash reductions, and both had CIs above zero, indicating high confidence that those ADAS feature sets are reducing all single-vehicle road-departure crashes. LDW had an estimated crash reduction of 3% (-2 to 8%), which is not necessarily different from zero. Though these effectiveness estimates were for vehicles equipped with the features, whether the features were in use at the time of crash is unknown. Therefore, the effectiveness estimates assume usage of the feature. If the feature is being used less, then the effectiveness will reflect that by being lower. The usage (and non-usage) of the feature is believed to have a bigger impact on lateral features' effectiveness than FCW and AEB [23] [24].

To understand the sensitivity of the estimated lateral ADAS feature reductions to the definition of the control crashes, PARTS estimated the reductions using an alternate control crash (see Appendix B). This analysis found that the reduction estimates for LDW were very similar when using the alternate control crash type. The crash reductions for LDW + LKA and LDW + LKA + LCA were slightly less but comparable when using the alternate control crash.

4.3.3 LDW/LKA/LCA Results for Injury Crashes

Focusing attention on injury crashes reduced the system-relevant crash sample sizes by about 70% (see Figure 4-5). This study found that the estimated reductions in injury single-vehicle road-departure crashes were very consistent for all feature sets but with widened CIs. LDW + LKA had an estimated reduction of 7% and, similarly, LDW + LKA + LCA had an estimated reduction of 8%. Although the estimates were very similar, the CI for LDW + LKA + LCA covered zero (i.e., was not necessarily effective), likely due to the reduced sample size. LDW had an estimated reduction of 5%, which was not necessarily different than zero.

4.3.4 LDW/LKA/LCA Results for Serious Crashes

The system-relevant serious single-vehicle road-departure crashes were about 5% of the total system-relevant crashes (see Figure 4-5). As expected, single-vehicle road-departure crashes (5% involve serious or fatal injury) lead to more severe injuries than front-to-rear crashes (1% involve serious or fatal injury). The subset of system-relevant crashes involving a serious or fatal injury produced a more limited sample size. For serious single-vehicle road-departure crashes, this study estimated reductions of 5% for LDW, 13% for LDW + LKA, and 16% for LDW + LKA + LCA, all of which were not necessarily different from zero. This is likely from the widening of the CIs due to more limited sample sizes.

4.3.5 LDW/LKA/LCA Results by Condition

Similar to the process described above for FCW/AEB, PARTS investigated whether lateral ADAS feature effectiveness changed with respect to any of the covariates using BIC. This study found no interactions for LDW. For LDW + LKA, only sales type (fleet or retail) was identified by BIC for the all single-vehicle road-departure crashes and injury single-vehicle road-departure crashes models. This study found no interactions for LDW + LKA + LCA. For more information on interaction effects, see Appendix E.

5 Discussion

This PARTS study drew on data from 93 vehicle models for model years 2015 to 2020 that crashed in 13 states from January 2016 through August 2021. This level of collaborative data sharing and analysis by PARTS partners yielded one of the largest sample sizes of system-relevant crashes.

The focus of this study was on crash avoidance rather than crash mitigation. In many cases – almost half for FCW + AEB in front-to-rear crashes – the presence of ADAS features do prevent the crashes from happening. In many other cases, the crash is unavoidable and still occurs. Yet, ADAS can still assist by potentially making the crash less severe, with fewer and less serious injuries. In the future, PARTS will estimate crash mitigation separately from avoidance.

5.1 AEB/FCW (Front-to-rear Crashes)

This study estimated that when vehicles are equipped with FCW + AEB, they are 49% less likely to strike another vehicle in a front-to-rear crash. FCW + AEB effectiveness increases to 53% for crashes involving injury and was slightly reduced, to 42%, for the most serious (including fatal) crashes. The avoidance of about half of front-to-rear crashes across crash types is a remarkable achievement and demonstrates industry's voluntary and proactive commitment to safety [25]. Because drivers likely have FCW + AEB enabled at high rates [26] compared with other ADAS features, these estimates show the real-world effectiveness of AEB as a safety technology and that FCW + AEB is less sensitive to consumer acceptance.

When vehicles are equipped with FCW and not AEB, they are 16% less likely to strike another vehicle in a front-to-rear crash, indicating that safety technologies that actively intervene and automatically brake to help avoid a collision are much more effective than just alerting drivers of potential collisions ahead. The estimated reductions found in this study align well with past literature (see Appendix A), especially once accounting for CIs.

Because of the significant size and scope of the dataset, this study was able to assess effectiveness in a variety of environmental conditions and with regard to a variety of driver characteristics. The study demonstrated that AEB performs extremely well in all conditions, even when roadway, weather, and lighting conditions are not ideal. For example, AEB effectiveness is only reduced from 49% to 42% when comparing crashes that occur in daylight versus at dark. In addition, AEB effectiveness is only reduced from 49% to 44% when used on wet roads in bad weather as compared to on dry roads in good weather.

The goal of this study was not to explain the differences identified, but rather to indicate areas that require further research. The covariate analysis identified four areas that PARTS will explore in future iterations:

1. This study indicated that AEB effectiveness is lower for speed limits under 35 mph, particularly those under 25 mph, as compared to speed limits 35 mph and above. Lower-speed crashes are less likely to be police-reported in some states, and vehicles in lower-speed crashes may not have reached their minimum activation speed for AEB. In the

future, PARTS may incorporate information about the ODD for ADAS systems to analyze only those situations in which the systems are designed to function.

2. This study indicated that AEB effectiveness is lower as the age of drivers increased, 44% for drivers aged 55–64, 42% for drivers 65–74, and down to 34% for drivers over 75. More research is needed to understand these differences, though reasons could vary from driver adoption of ADAS, to driving behaviors, to types of crashes that younger vs. older drivers tend to be involved in.
3. This study indicated that AEB effectiveness is lower for all crashes occurring on curved road segments (34%) as compared to straight road segments (50%). This is an intuitive result, as vehicles may not be able to detect and classify the lead vehicle depending on the curvature of road. In the future, PARTS may integrate additional data sources that provide more accurate roadway information, including amount of curvature, to determine the type of curvature situations in which AEB is most and least effective.
4. This study indicated that AEB effectiveness is slightly lower for fleet vehicles than retail vehicles. Original reasons to analyze AEB effectiveness with respect to fleet vehicles were hypotheses that driver understanding and ability to use ADAS on their privately owned vs. rental or fleet vehicles may be different, and driver behavior may be different. More research is needed to better understand the population of fleet vehicles and their drivers to explain why AEB is less effective, though one hypothesis is that once a driver disables AEB in a fleet vehicle, it may become the new default state for subsequent renters. One limitation of this analysis is that data was not available to clarify whether the crashes occurred while the vehicle was still used as a fleet vehicle or after it had transitioned to private ownership.

In general, this study also found that the set of covariates analyzed were generally relevant, helpful in controlling for influential factors, and useful in detecting condition-specific effects. Based on their utility, the covariates used in this study should be included in future studies and refined as appropriate given additional data and model maturation. In particular, other studies using quasi-induced exposure should include crash year as a controlling factor.

Partners identified a number of priorities for expanding the FCW+AEB analysis in future iterations beyond those listed above. These include the following: (1) Understand unintended consequences, such as whether AEB-equipped vehicles are more likely to be in front-to-rear crashes; (2) Understand the distribution of the striking vs. struck vehicle, including by body type and/or mass, and explore how the severity of injuries vary with these differences; (3) Better understand how driver behavior, including risky behaviors, may impact results; (4) Determine how AEB effectiveness changes over the vehicle's lifecycle, especially accounting for vehicle service, maintenance, recalibrations of ADAS, or changing ownership; and (5) Consider effectiveness in other types of system-relevant crashes, such as head-on crashes and left turn across path crashes, as AEB functionality is expanded.

5.2 PAEB (Frontal Crashes with Non-motorists)

In this iteration of analysis, the sample sizes were too small to detect a statistically significant result for PAEB effectiveness. This is due to the limited number of these incidents in crash reports and the lower level of market penetration for PAEB as compared to AEB, particularly in recent model years. However, as part of the collaborative analytic process, government and industry partners along with MITRE refined how non-motorist crashes were identified and mapped to narrow the set to those that are most relevant, explored the dataset to better understand what types of crashes are represented in the data (including a comparison of pedestrian vs. non-motorist crashes), and tested several hypotheses and conditions using the same rigorous methods as used with the AEB analysis. This work represents a significant amount of learning and preparation for future iterations.

In the future, PARTS may expand its dataset and investigate the effectiveness of PAEB by incorporating more information about the non-motorist (type of non-motorist, child vs. adult, and their actions, condition, and visibility prior to crash), vehicle (e.g., headlight implementation, ODD for PAEB, weight, grill height), and the crash (e.g., speed, kinematics of the pedestrian strike) to improve the analysis. Understanding the trajectories of vehicles and pedestrians prior to a collision is essential for understanding crash outcomes. More research is needed to understand contributing factors to crashes involving non-motorists, such as how poor lighting and insufficient infrastructure intersect with driver behaviors (e.g., speeding, impairment) and pedestrian factors (e.g., wearing dark clothing, impairment).

5.3 LDW/LKA/LCA (Single-vehicle Road-departure Crashes)

The analysis found that ADAS features such as LDW + LKA, when working together, provide some safety benefit in reducing single-vehicle road-departure crashes. The study estimated that lane management feature sets (LDW + LKA and LDW + LKA + LCA) reduced crashes by about a tenth for all single-vehicle road-departure crashes (8% and 9% respectively). These feature sets had similar estimated reductions for injury single-vehicle road-departure crashes, although after accounting for uncertainty, there was a possibility of no effect for LDW + LKA + LCA on reducing injury crashes. For crashes with a serious injury, estimates of reduction were slightly higher (13% and 16%), but once accounting for uncertainty there was still the possibility of no effect, possibly due to limited sample sizes.

This study also estimated that LDW reduced single-vehicle road-departure crashes by about 5%, but accounting for uncertainty there was the possibility that LDW had no effect.

A significant limitation of the study is an assumption that if a vehicle is equipped with a feature, the driver has enabled that feature and it is activated at the time of crash. One possible reason for the lower effectiveness of LDW and LKA is that drivers may be turning off the systems 50% of the time [26] – if true, it shows that LDW and LKA effectiveness could be higher if people used them more. In the future, it is important to assess effectiveness once actual feature usage can be accounted for, and to explore why drivers are turning the systems off, including the types of alerts that are most and least annoying, and what can be done to encourage adoption.

Another limitation is that the study did not incorporate information about OEM-specific implementations of lane management systems, to include the type of warning systems (e.g., auditory vs. haptic feedback) or the ODD that defines the limits of that feature's functional capability. For example, PARTS partners recognized that systems are not designed to work at lower speeds. The expectation is that effectiveness rates would be more accurate in a future iteration that was narrowed to only crashes in which the technology was designed to operate.

This analysis was limited by lack of roadway information at the time of crash – for example, there was no information about the existence or condition of lane markings, the number of lanes, or the exact amount of road curvature to understand how these lane management features perform in the real world under different roadway conditions. In the future, PARTS may investigate ways to incorporate more information about the roadway into the analysis.

5.4 Summary of Study Limitations

This section summarizes the major limitations of this study, which have been discussed throughout the report.

First, this study accounts for vehicles that were equipped with ADAS features at the time of manufacture and does not account for actual ADAS usage. It does not capture when drivers have enabled or disabled ADAS features at the time of crash. These limitations likely affect effectiveness estimates of LDW, LKA, and LCA much more than FCW/AEB and PAEB.

Second, this study does not directly account for different driving behaviors and their effect on ADAS effectiveness. While the exact individual driver risk-taking profile and behaviors are unknown, PARTS included proxies, such as driver age, gender, and even vehicle model, as indicative of driver behavior.

Third, this study does not capture the variability in ADAS implementations across different OEMs, models, model years, and trimline-specific design and specifications. Further, this study did not incorporate data on each vehicle feature's ODD that defines the limits of that feature's functional capability to operate; rather, it assumed that if equipped, ODD parameters were met at the time of the crash.

Fourth, the use of police-reported crash reports as a primary source of data presents a series of well-known challenges. KABCO [5], the framework for categorizing injury information used within the crash database, may not reflect precisely the injuries, injury type, or body region compared against the Abbreviation Injury Scale [16] [17] [18] [19]. Some information documented in the crash report is subjective by the police officer and may be reported inconsistently between officers and states (e.g., driver distraction at time of crash). Crash reports may have limited or no information on relevant factors (e.g., actual speed of the vehicle, road infrastructure that may impact the effectiveness of these systems). These limitations with police-reported crash data are known and generally accepted by this and other related studies, and do not present an outsize concern regarding the results.

Finally, results may not be representative of the United States. While PARTS took care to capture census data from a diverse set of 13 states and many vehicles, this data on state-level crashes and associated vehicles may not be nationally representative. See Appendix G for a comparison between the study population and a national sample. In the future, once sample sizes are sufficient, PARTS may analyze ADAS effectiveness using data from a national representative database, such as NHTSA's Crash Report Sampling System (CRSS).

5.5 Suggestions for Future Research

The data sharing and analysis partnership of PARTS is truly unique. This study was able to be completed because of each partner's willingness to share data and collaborate on the analysis, a commitment that the partners remain dedicated to and plan to further. PARTS plans to reiterate and expand this study as ADAS features continue to be deployed.

In future iterations, PARTS will seek to incorporate data from additional partners and states to expand the sample sizes and increase the representativeness of the study. Industry partners may provide data from more vehicle models and model years, on more ADAS features, as well as information about OEM-unique implementations of those features. In addition, NHTSA is currently in the process of refining and expanding EDT.[11] This PARTS study is one of the first large-scale analysis efforts to use EDT-driven crash data. As states are added, PARTS will be an immediate beneficiary, and its studies will constitute an increasingly nationally represented view of traffic crashes. As sample sizes increase, especially for injury and serious crashes, it is expected that uncertainty in the estimates will decrease (i.e., narrower CIs), which could cause an increase of power in detecting effectiveness.

In addition to expanded crash data and OEM-provided vehicle equipment data, a key opportunity is to explore and potentially incorporate other data sources, such as vehicle-based telematics, to better understand actual ADAS feature usage and activation, including whether and how features intervene in various situations. In addition, PARTS and traffic safety researchers may seek better, more comprehensive injury outcome data, to include relevant Emergency Medical Services (EMS) and hospital record data for both drivers and passengers involved in crashes, to enhance understanding of outcomes in a variety of situations.

In future iterations, PARTS may also adjust its analytic methodology to address the challenges of estimating effectiveness that come once ADAS features become standard equipment on vehicles. In the PARTS study, the difference between the set of equipped and unequipped vehicles became starker as the model year increased, which made it more challenging to accurately estimate effectiveness without confounding factors influencing results.

PARTS, as a data sharing public-private partnership, is one-of-its-kind and innovative, continuously proving out new approaches for collaborating on safety. Learnings from PARTS will support improvement in ADAS technologies to have maximum impact on roadway safety. Working together, government and industry can contribute to enhancing the safety of our roads.

[11] The Bipartisan Infrastructure Law [28] compels NHTSA to provide state grants to further facilitate the electronic transfer of data to the agency.

Acronyms

Term	Definition
AAA	American Automobile Association
ADAS	Advanced Driver Assistance Systems
ADS	Automated Driving Systems
AEB	Automatic Emergency Braking
BIC	Bayesian Information Criterion
BSW	Blind Spot Warning
CI	Confidence Interval
CRSS	Crash Report Sampling System
CSC	Consolidated State Crash
EDT	Electronic Data Transfer [system]
EMS	Emergency Medical Services
FARS	Fatality Analysis Reporting System
FCA	Fiat Chrysler Automobiles
FCW	Forward Collision Warning
GM	General Motors
HLDI	Highway Loss Data Institute
IIHS	Insurance Institute for Highway Safety
LCA	Lane Centering Assistance
LDW	Lane Departure Warning
LKA	Lane Keeping Assistance
NHTSA	National Highway Traffic Safety Administration
ODD	Operational Design Domain
OEM	Original Equipment Manufacturer
PAEB	Pedestrian Automatic Emergency Braking
PARTS	Partnership for Analytics Research in Traffic Safety
SUV	Sport Utility Vehicle
USDOT	United States Department of Transportation
UMTRI	University of Michigan Transportation Research Institute
VIN	Vehicle Identification Number

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Appendix A. Related Research

PARTS conducted a literature review to identify other relevant research and determine how that might inform the direction and methods of this research. In addition, the relevant research identified here assisted with comparing and validating results.

Literature on FCW/AEB Effectiveness

Table A-1 and the following paragraphs summarize research studies of FCW and FCW +AEB real-world effectiveness.

Table A-1 Comparison of FCW/AEB Studies

Study → Attribute ↓	UMTRI [9]	Toyota/Impact Research/Toyota 2021 [10]	IIHS 2017 [12]
OEMs Represented	1 (GM)	1 (Toyota)	5 (Honda incl. Acura, Fiat Chrysler, Mercedes-Benz, SUBARU, Volvo)
Model Years Represented	2013–2020	2015–2018	2008–2015
ADAS Features Studied	FCW FCW + AEB	FCW + AEB	FCW FCW + AEB
Count of States in Crash Data	14	8	22
Source of Crash Data	State Crash Data	State Crash Data	State Crash Data
Conceptual Notion of System Relevant Crash	Front-to-rear Striking	Front-to-rear Striking	Front-to-rear Striking
Linked Relevant Crashes (All)	54,412	92,876	23,649
Linked Relevant Crashes (ADAS only)	FCW 9,408 FCW and AEB 7,055	FCW and AEB 30,056	FCW 833 FCW and AEB 444
Statistical Approach	Logistic Regression	Logistic Regression	Poisson Regression
Exposure Metric	Quasi-induced Exposure	Quasi-induced Exposure	Vehicle Days Insured
Comparison Group	Unequipped	Unequipped	Unequipped
All System-relevant Crashes FCW Effectiveness	20% (15 to 24%)*	–	27% (19 to 34%)
All System-relevant Crashes FCW+AEB Effectiveness	41% (Not Reported)* Camera 40% (37 to 43%)* Camera/Radar 45% (40 to 49%)*	43% (39 to 46%)	50% (34 to 62%)

Study → Attribute ↓	UMTRI [9]	Toyota/Impact Research/Toyota 2021 [10]	IIHS 2017 [12]
Injury System-relevant Crashes FCW Effectiveness	25% (15 to 35%)*	–	20% (2 to 34%)
Injury System-relevant Crashes FCW+AEB Effectiveness	55% (Not Reported)* Camera 55% (49 to 61%)* Camera/Radar 58% (50 to 65%)*	–	56% (24 to 74%)

*Table notes: By convention, this PARTS report shades results gray when the associated CI includes zero or there is insufficient statistical significance. * CI imputed visually from graph*

The effectiveness of FCW and FCW + AEB has been studied extensively by UMTRI [6] [8] [9]. Table A-1 and this discussion focus on the latest research by UMTRI [9], which uses the same methodology as PARTS of linking crash data to vehicles by VIN and using quasi-induced exposure in addition to logistic regression. This UMTRI study estimated effectiveness of a single OEM, while the PARTS study included multiple OEMs. Additional differences existed in the source of some data elements (e.g., state crash data from sources other than NHTSA), the exact data used (e.g., different model years, different states), and details of implementation (e.g., covariates included, specification of covariate levels, exact definition of crash types where injury crashes used “B” or higher KABCO injuries, while PARTS looked at “C” or higher).

Impact Research/Toyota 2021 [10] studied the effectiveness of FCW + AEB, but not FCW alone, [10] and used the same methodology as PARTS of linking crash and vehicle data through VIN and using quasi-induced exposure in addition to logistic regression. The study estimated effectiveness of a single OEM, while the PARTS study included multiple OEMs. Additional differences existed in the source of some data elements, exact data used (e.g., older model years; different states), and details of implementation (e.g., controlled for a smaller set of covariates; different specification of covariate levels; definition of crash type where PARTS more precisely defined system-relevant crashes such as by removing crashes involving more than 2 vehicles).

IIHS 2017 [12] studied the effectiveness of FCW and FCW + AEB and used a different methodology than PARTS, namely a Poisson regression with the exposure being vehicle days insured in 6-month increments. Similar to PARTS, the IIHS study looked at the effectiveness of multiple OEMs, but the exact OEMs and vehicle models differed. Additional differences existed in the source of some data elements, exact data used, and details of implementation.

Literature on PAEB Effectiveness

Table A-2 and the following paragraphs summarize recent research studies of PAEB real-world effectiveness.

Table A-2 Comparison of PAEB Studies

Study → Attribute ↓	UMTRI [9]	Impact Research/Toyota [11]	IIHS [14]
OEMs Represented	1 (GM)	1 (Toyota)	8 (Honda incl. Acura; GM incl. Buick, Cadillac, Chevrolet, GMC; Hyundai; Kia; Mazda; Mitsubishi; Nissan; SUBARU)
Model Years Represented	2013–2020	2015–2018	2017–2020
ADAS Features Studied	PAEB	PAEB	PAEB
Count of States in Crash Data	14	8	18
Source of Crash Data	State Crash Data	State Crash Data	State Crash Data
Conceptual Notion of System Relevant Crash			
Linked Relevant Crashes (All)	1,298	1,864	646
Linked Relevant Crashes (ADAS only)	PAEB 79	PAEB 547	PAEB Not Reported (~30% of system-relevant for Poisson regression)
Statistical Approach	Logistic Regression	Cox Proportional Hazard Regression	Logistic Regression (focus of this table) and Poisson Regression
Exposure Metric	Quasi-induced Exposure	Vehicle days since sale or end of study	Quasi-induced Exposure
Comparison Group	Unequipped	Unequipped	Unequipped
All System-relevant Crashes PAEB Effectiveness	23% (0 to 40%)*	16% (-6 to 31%)*	25% (5 to 41%)
Injury System-relevant Crashes PAEB Effectiveness	–	–	29% (9 to 45%)
Serious System-relevant Crashes PAEB Effectiveness	–	–	3% (-43 to 40%)

*Table notes: By convention, this PARTS report shades results gray when the associated CI includes zero or there is insufficient statistical significance. * CI imputed visually from graph*

UMTRI [9], in the same study that estimated FCW and FCW + AEB effectiveness, also studied the effectiveness of PAEB at reducing pedestrian crashes. The study for PAEB had many of the same similarities and differences to PARTS as discussed above for FCW and FCW + AEB. Other important differences from PARTS are as follows. The system-relevant crash definition differed by including multi-vehicle accidents and restricting the analyses to crashes at speed limits less than 50 miles per hour.[12] UMTRI studied PAEB for all crashes (i.e., those causing injury and property damage). Because this likely includes mostly injury crashes, it is reasonable to compare the injury-only PARTS results with the UMTRI results.

Impact Research/Toyota [11] estimated the effectiveness of PAEB using a different methodology than PARTS. The methodology was survival (i.e., time-to-event) analysis, specifically a Cox proportional hazard regression, with days from retail to crash as the exposure metric. Additional differences existed in the source of some data elements, exact data used, and details of implementation. The study did not look at subsets of crashes by injury.

IIHS [14] estimated PAEB effectiveness using two methodologies: (1) quasi-induced exposure via logistic regression and (2) Poisson regression with insured vehicle year as the exposure metric. This discussion focuses on the results from the quasi-induced exposure since it more closely aligns with the PARTS study methodology. IIHS looked at the effectiveness for all crashes, injury, and serious crashes. The study looked at the effectiveness of multiple OEM systems, similar to PARTS, but the OEMs and vehicle models differed. Additional differences existed in the source of some data elements, exact data used, and details of implementation (e.g., including multiple vehicle crashes and not filtering on point of contact). Some of the effectiveness estimates differed from PARTS, especially when looking at the targeted hypotheses of whether effectiveness differed by light condition and for turning vehicles.

Literature on LDW/LKA/LCA Effectiveness

Table A-3 and the following paragraphs summarize recent research studies of LDW, LDW + LKA, and LDW + LKA + LCA real-world effectiveness.

Table A-3 Comparison of LDW/LKA/LCA Studies

Study → Attribute ↓	UMTRI [9]	Impact Research/Toyota [11]	IIHS 2018 [13]
OEMs Represented	1 (GM)	1 (Toyota)	6 (GM (Buick, Cadillac, Chevrolet, GMC), Honda, Mazda, Mercedes-Benz, SUBARU, Volvo)
Model Years Represented	2013–2020	2015–2018	2008–2016

[12] Older studies used a 35 miles per hour threshold and only recently moved up the threshold, suggesting the technology is becoming more effective.

Study → Attribute ↓	UMTRI [9]	Impact Research/Toyota [11]	IIHS 2018 [13]
ADAS Features Studied	LDW LDW + LKA	LDW + LKA	LDW
Count of States in Crash Data	14	8	25
Source of Crash Data	State Crash Data	State Crash Data	State Crash Data
Linked Relevant Crashes (All)	12,105	6,489	5433
Linked Relevant Crashes (ADAS only)	LDW 1810 LDW + LKA 2106	LDW + LKA 2077	LDW only 1684
Statistical Approach	Logistic Regression	Cox Proportional Hazard Regression	Poisson Regression
Exposure Metric	Quasi-induced Exposure	Vehicle Days since sale or end of study	Insured vehicle days
Comparison Group	Unequipped	Unequipped	Unequipped
All System-relevant Crashes LDW Effectiveness	8% (0 to 15%)*	–	11% (1 to 20%)
All System-relevant Crashes LDW+LKA or LDW+LKA+LCA Effectiveness	17% (10 to 25%)*	9% (1 to 16%)	–
Injury System-relevant Crashes LDW Effectiveness	-3% (-25 to 15%)*	–	21% (-2 to 38%)
Injury System-relevant Crashes LDW+LKA or LDW+LKA+LCA Effectiveness	21% (8 to 30%)*	–	–

*Table Notes: By convention, this PARTS report shades results gray when the associated CI includes zero or there is insufficient statistical significance. * CI imputed visually from graph*

In the same study that estimated FCW, FCW + AEB, and PAEB effectiveness, UMTRI [9] also studied the effectiveness of LDW and LDW + LKA at reducing single-vehicle road departures along with other crash types. The study for LDW and LKA had the same similarities and differences to PARTS as discussed above for AEB and FCW, with the exception that Road Alignment was included as a covariate in the LDW and LDW + LKA analysis. The system-relevant crash definition differed by restricting analysis to only crashes at speed limits greater than 30 miles per hour and not filtering on vehicle maneuver.

Impact Research/Toyota [11], in the same study that estimated PAEB effectiveness above, also studied effectiveness of LDW + LKA, but not LDW alone. The study for LDW + LKA had the same similarities and differences to PARTS as when the research was discussed for PAEB. The system-relevant crash definition differed by only including “ran off the road” events, compared to PARTS including a larger set of events (i.e., "ran off the road," "cross centerline," "cross median," "collision with fixed objects," or "rollover") with additional filters on vehicle maneuvers.

IIHS 2018 [13] studied the effectiveness of LDW alone (not LKA or LCA) on reducing single-vehicle road departures, head-on, and sideswipe same-direction crashes combined. The methodology used was very similar to that used by IIHS 2017 [12] to study FCW and FCW + AEB effectiveness. The study used a different methodology than PARTS, namely a Poisson regression with the exposure being vehicle days insured in 6-month increments. The study looked at the system effectiveness of multiple OEMs, similar to PARTS, but the exact OEMs and vehicle models differed. Additional differences existed in the source of some data elements, exact data used, and details of implementation.

Appendix B. Alternate Control Sensitivity Investigation

PARTS investigated the sensitivity of ADAS features' estimated reductions to the choice of control crash by additionally estimating reductions using an alternative control crash and comparing those with the primary control crash used in this study (front-to-rear struck).

PARTS defined the alternate control crash vehicles as selected participating OEM vehicles that were in angled collisions at intersections. PARTS identified these vehicles among all participating OEM vehicles associated with crashes by using all of the following selection criteria (logical AND):

- Manner of crash was Angle, Front-to-side.
- Crash Intersection was labeled as occurring at intersection.

The presence of ADAS features was not expected to impact the frequency of such collisions.

FCW/AEB

The estimated reductions for FCW and FCW + AEB were similar when measured using the alternative angled intersection control and when measured using the primary front-to-rear struck control (see Table B-1).

Table B-1 Comparison of FCW/AEB Effectiveness on All Crashes by Control

ADAS Feature	All Crashes Reduction with Angled Intersection Control	All Crashes Reduction with Front-to-rear Struck Control
FCW	16% (12 to 20%)	16% (13 to 20%)
FCW + AEB	46% (45 to 48%)	49% (48 to 50%)

PAEB

The estimated reductions for PAEB were similar when measured using the angled intersection and the front-to-rear struck controls (see Table B-2).

Table B-2 Comparison of PAEB Effectiveness on Injury Crashes by Control

ADAS Feature	Injury Crashes Reduction with Angled Intersection Control	Injury Crashes Reduction with Front-to-rear Struck Control
PAEB	3% (-6 to 11%)	4% (-6 to 12%)

LDW/LKA/LCA

The estimated LDW reductions were similar when measured using the alternate and primary controls. However, the estimated reductions for LDW + LKA and LDW + LKA + LCA were not similar based on control used, as shown in Table B-3.

Table B-3 Comparison of LDW/LKA/LC Effectiveness on All Crashes by Control

ADAS Feature	All Crashes Reduction with Angled Intersection Control	All Crashes Reduction with Front-to-rear Struck Control
LDW	2% (-4 to 7%)	3% (-2 to 8%)
LDW + LKA	2% (-2 to 6%)	8% (5 to 12%)
LDW + LKA + LCA	4% (-2 to 9%)	9% (4 to 14%)

Appendix C. Other System-relevant Crashes for LDW/LKA/LCA

In addition to single-vehicle road-departure crashes, PARTS estimated lateral ADAS features' effectiveness at reducing sideswipe same-direction and opposite-direction crashes. Sideswipe same-direction and opposite-direction (including head-on) crash types had limitations with respect to identifying the initiating vehicle in the crash (i.e., vehicle leaving its lane). See the crash mappings and estimated effectiveness below.

This PARTS study found that lane management (LDW, LKA, and LCA) feature effectiveness for sideswipe same-direction and opposite-direction was similar or lower than for single-vehicle road-departure crashes, which could be due to including vehicles where lane management features would not be expected to reduce collisions (i.e., vehicles not leaving their lane). PARTS added BSW as a main effect for sideswipe same-direction but did not include it as a main effect for opposite-direction crashes. The reason PARTS included BSW was not to estimate BSW effectiveness but rather to control for BSW influence while estimating effectiveness for LDW, LKA, and LCA.

Sideswipe Same-direction Crashes

PARTS used the following selection criteria to identify sideswipe same-direction crashes (logical AND):

- Manner of crash was identified as Sideswipe, Same Direction.
- Vehicle maneuver at the time of crash was either: going straight, negotiating a curve, leaving traffic lane, or ran off road.

As shown in Table C-1, LDW + LKA reduced the likelihood of all crashes and injury crashes for sideswipe same-direction collisions compared against vehicles not equipped with any of the three lateral features. Other findings were not necessarily different from zero.

Table C-1 Sideswipe Same-direction Results

ADAS Feature	All Crashes	Injury Crashes	Serious Crashes
LDW	0% (-3 to 3%)	-1% (-9 to 6%)	19% (-6 to 39%)
LDW + LKA	5% (3 to 7%)	8% (3 to 12%)	-5% (-28 to 13%)
LDW + LKA + LCA	-1% (-4 to 2%)	1% (-6 to 8%)	9% (-19 to 30%)

Sample sizes for the analysis of sideswipe same-direction for all, injury, serious, and control crashes are shown in Table C-2.

Table C-2 Sample Sizes for Sideswipe Same-direction Analysis

ADAS Feature	All Crash Vehicles	Injury Crash Vehicles	Serious Crash Vehicles	Control Crash Vehicles
No LDW, No LKA, No LCA	124,714	16,255	1,070	275,178
LDW	8,829	1,093	73	22,162
LDW + LKA	27,343	3,306	245	70,007
LDW + LKA + LCA	13,776	1,764	103	34,660

Opposite-direction Crashes

PARTS used the following selection criteria to identify opposite-direction crashes (logical AND):

- Manner of crash was Opposite Direction or Front-to-front.
- Vehicle maneuver at the time of crash was either: going straight, negotiating a curve, leaving traffic lane, or ran off road.

As shown in Table C-3, LDW + LKA reduced the likelihood of all crashes and injury crashes for opposite-direction collisions compared against vehicles not equipped with any of the three lateral features. Other results are not necessarily different from zero.

Table C-3 Sideswipe Opposite-direction Results

ADAS Feature	All Crashes Reduction	Injury Crashes Reduction	Serious Crashes Reduction
LDW	0% (-5 to 5%)	3% (-5 to 10%)	-1% (-17 to 14%)
LDW + LKA	8% (4 to 11%)	7% (2 to 12%)	-1% (-13 to 10%)
LDW + LKA + LCA	3% (-2 to 8%)	5% (-3 to 11%)	-4% (-22 to 12%)

Sample sizes for analysis of opposite-direction for all, injury, serious, and control crashes are shown in Table C-4.

Table C-4 Sample Sizes for Opposite-direction Analysis

ADAS Feature	All Crash Vehices	Injury Crash Vehicles	Serious Crash Vehicles	Control Crash Vehicles
No LDW, No LKA, No LCA	37,196	15,020	3,155	275,178
LDW	2,716	1,079	246	22,162
LDW + LKA	7,282	2,938	617	70,007
LDW + LKA + LCA	3,565	1,481	295	34,660

Appendix D. Illustration of Quasi-induced Exposure

To provide more insight into quasi-induced exposure, see Table D-1, which is a mock data example of quasi-induced exposure calculations and is not meant to represent study performance in any way.

Table D-1 Quasi-induced Exposure Mock Data Example

	Equipped vehicles	Non-equipped vehicles
System-relevant crashes	A = 4	B = 2
Control crashes	C = 16	D = 6

The odds of an equipped vehicle being in a system-relevant crash is

$$OOoooooo = AA/CC = 4/16 = 0.25.$$

By contrast, the odds of an unequipped vehicle being in a system-relevant crash is

$$OOoooooo = BB/DD = 2/6 = 0.33.$$

To compare equipped against unequipped, look at the odds ratio

$$OOoooooo\ RRRRRRRRLL = \frac{AA/CC}{BB/DD} = \frac{4/16}{2/6} = \frac{0.25}{0.33} = 0.76$$

If the odds ratio of equipped to unequipped is less than one (<1), then that indicates the ADAS feature is effectively reducing crashes. The lower the odds ratio, the more effective the ADAS feature. For relatively rare outcomes, as is assumed for crashes here, the odds ratio approximates the risk ratio.

To formulate ADAS effectiveness more intuitively, so that a higher value indicates greater effectiveness, PARTS applies the formula below to convert odds ratio into percent reduction.

$$PPeePPEEeeEERRRRLLee\ PPeeooRREERRRRLLEE = (1 - OOoooooo\ RRRRRRRRLL) * 100 = (1 - 0.76) * 100 = 24\%$$

PARTS carried out the estimation of ADAS effectiveness given various factors through the statistical modeling framework of a logistic regression (see Section 3.2.2), as has been done in other traffic safety studies [21] [10] [9].

Appendix E. All Identified Interactions

This appendix presents results from all interactions PARTS identified for this study, for the three major areas of focus: front-to-rear crashes for FCW/AEB, single-vehicle road-departure crashes for LDW/LKA/LCA, and non-motorist crashes for PAEB.

PARTS not only wanted to understand the effectiveness of ADAS features but also whether the effectiveness changed for specific conditions or populations. To understand the change in effectiveness, PARTS individually interacted each covariate with an ADAS feature, and used BIC to identify when the interaction added meaningful information (i.e., identify when ADAS feature effectiveness changed with respect to covariate).

Interactions for FCW+AEB

This PARTS analysis found that FCW does not interact with anything, so only covariates' interactions on FCW + AEB effectiveness are summarized in Table E-1. Where factors have an identified interaction for both all front-to-rear crashes and injury front-to-rear crashes, the magnitude and direction of the effect are similar.

Table E-1 FCW + AEB Factor Interactions on Effectiveness

	Factor	All Front-to-rear Crashes	Injury Front-to-rear Crashes	Serious Front-to-rear Crashes
Driver	Driver Age	Change	No Change	No Change
	Alcohol/Drugs	No Change	No Change	No Change
	Distracted	No Change	No Change	No Change
	Driver Gender	No Change	No Change	No Change
Environment	Weather	Change	Change	No Change
	Road Surface Condition			
	Light Condition	Change	Change	No Change
	Roadway Alignment	Change	Change	No Change
	Intersection	Change	No Change	No Change
Crash	Crash State	No Change	No Change	No Change
	Crash Year	No Change	No Change	No Change
	Speed Limit	Change	No Change	No Change
Vehicle	Sales Type (Fleet vs. Retail)	Change	Change	No Change
	Vehicle Segment	No Change	No Change	No Change
	Vehicle Model Year	No Change	No Change	No Change

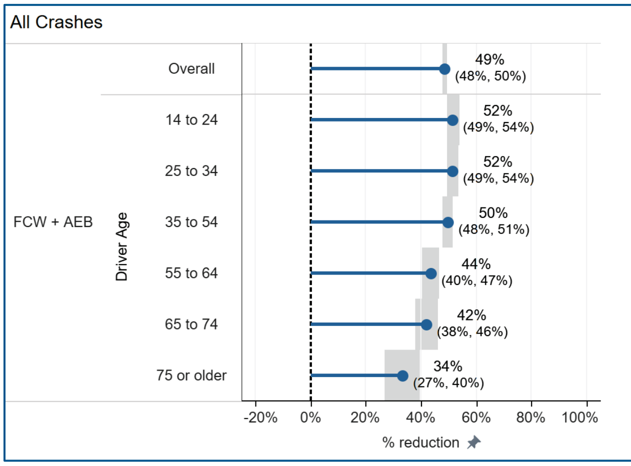
There may be other covariates for which changes in effectiveness exist but were not identified due to insufficient statistical power because of smaller sample sizes and the conservativeness of BIC. This is particularly true for FCW alone (where the sample size is much smaller than for

FCW + AEB) and given that the number of system-relevant crashes is reduced for injury crashes and serious crashes. Additionally, different specifications of the covariate levels (e.g., combining levels to cut down on number of parameters being added), which PARTS did not explore, may lead to identification by BIC.

The way interactions caused effectiveness to change generally aligned with the PARTS partners' intuition for many of the covariates identified by BIC.

Driver Age Interaction for Front-to-rear Crashes

In line with PARTS partner intuition (e.g., there are age-correlated reductions in driver response time), the effectiveness of FCW + AEB tends to be lower as the driver age increases, as shown in Figure E-1.

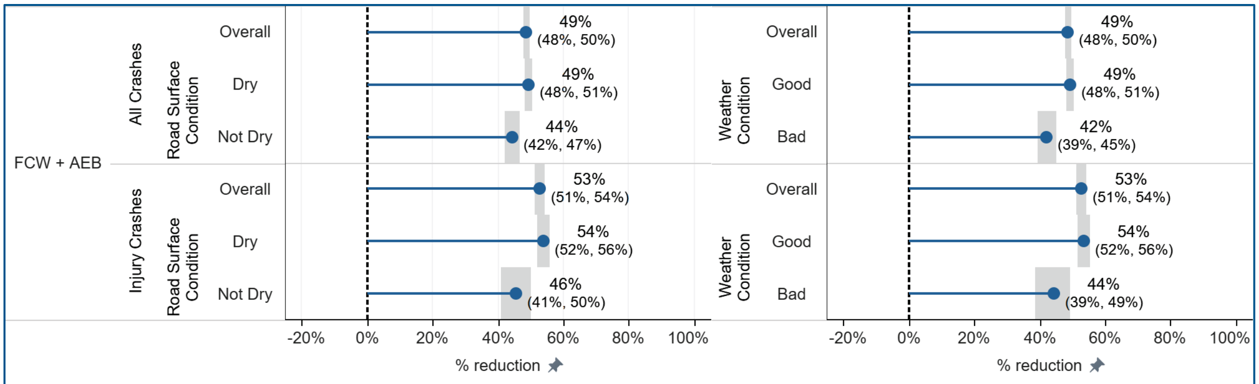


		System Relevant	Control
14-24	Neither	43,250	31,171
	FCW + AEB	8,125	13,889
25-34	Neither	49,241	60,540
	FCW + AEB	9,597	28,481
35-54	Neither	51,128	100,767
	FCW + AEB	12,269	55,776
55-64	Neither	15,287	35,393
	FCW + AEB	4,376	21,223
65-74	Neither	8,388	18,148
	FCW + AEB	3,048	13,091
75+	Neither	4,115	5,938
	FCW + AEB	1,882	4,697

Figure E-1 Reduction in Front-to-rear Crashes by Driver Age

Weather/Road Surface Interaction for Front-to-rear Crashes

In line with PARTS partner intuition, the effectiveness of FCW + AEB tends to be lower when the weather is bad and the road surface is wet, though all braking is less effective in those conditions (see Figure E-2). Note that weather conditions and road surface conditions are highly correlated, which makes it difficult to separate those covariates. Therefore, PARTS presents the change in FCW + AEB effectiveness for both of those covariates at the same time. It is possible that additional ADAS sensor considerations affect effectiveness if there is cloud cover or poor lighting conditions.

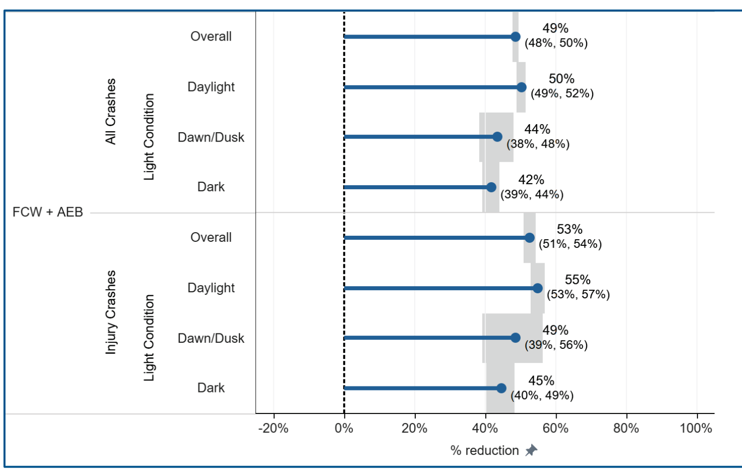


			Sample Size: System Relevant	Sample Size: Control				Sample Size: System Relevant	Sample Size: Control
All Crashes	Dry	Neither	147,768	209,998	All Crashes	Good Weather	Neither	154,090	221,072
		FCW + AEB	33,491	114,958			FCW + AEB	34,889	120,687
	Wet	Neither	23,641	41,959		Bad Weather	Neither	17,319	30,885
		FCW + AEB	5,806	22,199			FCW + AEB	4,408	16,470
Injury Crashes	Dry	Neither	36,286	209,998	Injury Crashes	Good Weather	Neither	37,609	221,072
		FCW + AEB	7,382	114,958			FCW + AEB	7,675	120,687
	Wet	Neither	5,154	41,959		Bad Weather	Neither	3,831	30,885
		FCW + AEB	1,216	22,199			FCW + AEB	923	16,470

Figure E-2 Reduction in Front-to-rear Crashes by Weather and Road Condition

Light Condition Interaction for Front-to-rear Crashes

In line with PARTS partner intuition, FCW + AEB was more effective in daylight conditions than dawn/dusk or dark conditions (see Figure E-3).

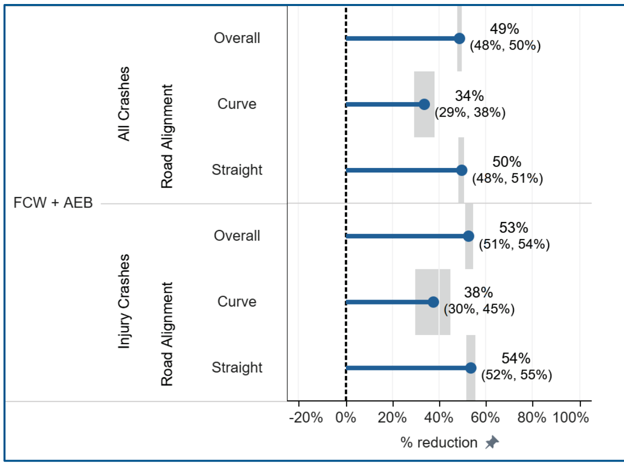


			System Relevant	Control
All Crashes	Daylight	Neither	133,868	197,791
		FCW + AEB	29,970	109,469
	Dawn/Dusk	Neither	6,670	10,147
		FCW + AEB	1,586	5,150
	Dark	Neither	30,871	44,019
		FCW + AEB	7,741	22,538
Injury Crashes	Daylight	Neither	30,879	197,791
		FCW + AEB	6,147	109,469
	Dawn/Dusk	Neither	1,617	10,147
		FCW + AEB	349	5,150
	Dark	Neither	8,944	44,019
		FCW + AEB	2,102	22,538

Figure E-3 Reduction in Front-to-rear Crashes by Light Condition

Roadway Alignment Interaction for Front-to-rear Crashes

In line with PARTS partner intuition, FCW + AEB effectiveness is lower when the crash occurs at a road that is curved compared to when the crash occurs on a road that is straight (see Figure E-4).

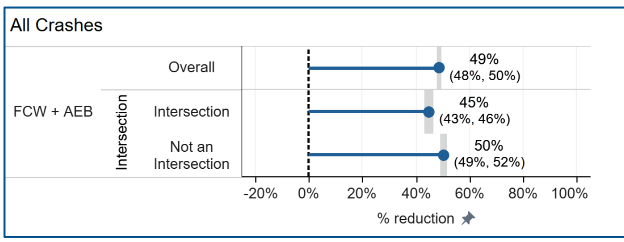


			System Relevant	Control
All Crashes	Curve	Neither	9,253	12,731
		FCW + AEB	2,855	7,027
	Straight	Neither	162,156	239,226
		FCW + AEB	36,442	130,130
Injury Crashes	Curve	Neither	2,142	12,731
		FCW + AEB	612	7,027
	Straight	Neither	39,298	239,226
		FCW + AEB	7,986	130,130

Figure E-4 Reduction in Front-to-rear Crashes by Roadway Alignment

Intersection Interaction for Front-to-rear Crashes

In line with PARTS partner intuition, FCW + AEB effectiveness is lower when the crashes occur at an intersection compared to crashes that do not occur at an intersection (see Figure E-5).

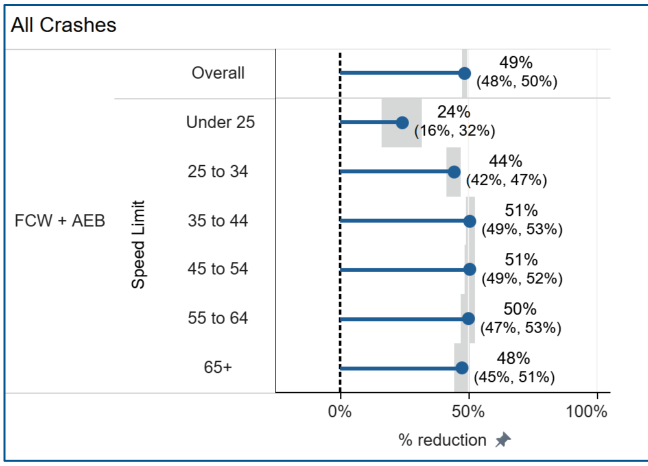


		System Relevant	Control
Intersection	Neither	53,513	80,451
	FCW + AEB	13,031	43,500
Not an Intersection	Neither	117,896	171,506
	FCW + AEB	26,266	93,657

Figure E-5 Reduction in All Front-to-rear Crashes by Intersection Condition

Speed Limit Interaction for Front-to-rear Crashes

An instance where the change in effectiveness was less intuitive to PARTS partners was with respect to speed limit (see Figure E-6). For speed limits under 25, a large drop in effectiveness is observed. These lower speed limit cases need to be investigated in more detail to understand if this is a true phenomenon, driven by a confounding factor such as aspects of the roads with speed limits under 25, or an artifact of the crash data itself.

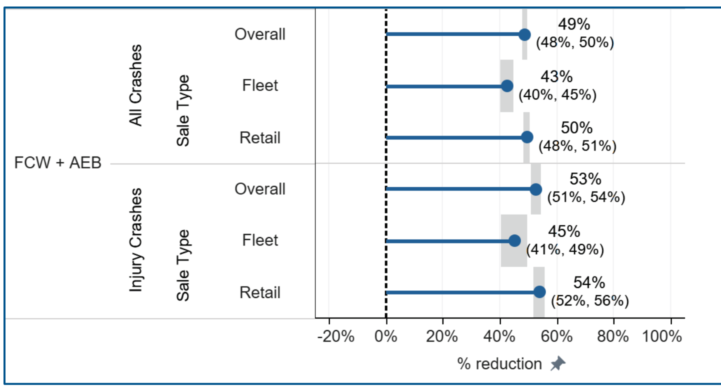


		System Relevant	Control
25-34 MPH	Neither	24,381	36,754
	FCW + AEB	5,786	19,188
35-44 MPH	Neither	51,426	77,441
	FCW + AEB	11,186	41,771
45-54 MPH	Neither	49,653	73,294
	FCW + AEB	11,311	40,805
55-64 MPH	Neither	23,261	33,284
	FCW + AEB	5,045	17,715
< 25 MPH	Neither	4,334	6,227
	FCW + AEB	1,561	3,535
> 65 MPH	Neither	18,354	24,957
	FCW + AEB	4,408	14,143

Figure E-6 Reduction in All Front-to-rear Crashes by Speed Limit

Sales Type Interaction for Front-to-rear Crashes

In line with PARTS partner intuition, FCW + AEB effectiveness is lower for vehicles sold as fleet vehicles compared to vehicles sold as retail (see Figure E-7).



			System Relevant	Control
All Crashes	Fleet	Neither	28,886	36,175
		FCW + AEB	6,456	16,967
	Retail	Neither	142,523	215,782
		FCW + AEB	32,841	120,190
Injury Crashes	Fleet	Neither	6,920	36,175
		FCW + AEB	1,481	16,967
	Retail	Neither	34,520	215,782
		FCW + AEB	7,117	120,190

Figure E-7 Reduction in Injury Front-to-rear Crashes by Sales Type

PAEB Interactions

This PARTS analysis found that PAEB does not interact with anything.

LDW/LKA/LCA Interactions

PARTS used BIC to investigate whether lateral ADAS feature effectiveness changed with respect to any of the covariates using BIC (see Table E-2). This study found no interactions for LDW or LDW + LKA + LCA. BIC only identified sales type (fleet or retail) for LDW + LKA for the all and injury single-vehicle road-departure crash models.

Table E-2 LDW + LKA Factor Interactions on Effectiveness

	Fact or	All crashes	Injury Crashes	Fatal Crashes
Driver	Driver Age	No Change	No Change	No Change
	Alcohol/Drugs	No Change	No Change	No Change
	Distracted	No Change	No Change	No Change
	Driver Gender	No Change	No Change	No Change
Environment	Weather Road Surface Condition	No Change	No Change	No Change
	Light Condition	No Change	No Change	No Change
	Roadway Alignment	No Change	No Change	No Change
	Intersection	No Change	No Change	No Change
Crash	Crash State	No Change	No Change	No Change
	Crash Year	No Change	No Change	No Change
	Speed Limit	No Change	No Change	No Change
Vehicle	Sales Type (Fleet vs. Retail)	Change	Change	No Change
	Vehicle Segment	No Change	No Change	No Change
	Vehicle Model Year	No Change	No Change	No Change

There may be other covariates for which changes in effectiveness exist but are unable to be identified due to lacking power (i.e., not detecting an effect that is present) because of smaller sample sizes associated with single-vehicle road-departure crashes and the conservativeness of BIC. This concern about lacking power to detect effectiveness change with respect to a covariate becomes greater when sample size decreases, when looking at a subset of crashes involving an injury, and even further for crashes involving a serious or fatal injury.

Due to the PARTS information protection protocol regarding attribution of results (e.g., suppress result when fewer than three entities comprise the result), detailed results on interactions for LDW/LKA/LCA are not presented.

Appendix F. Model Fit Statistics

This section presents model fit statistics for the logistic regressions of the PARTS study, by ADAS feature set (front-to-rear, non-motorist, single-vehicle road-departure) and crash type (all, injury, serious).

FCW/AEB Logistic Regression Models

The deviance, degrees of freedom, and BIC statistics are presented below for FCW/AEB logistic regression models for all front-to-rear crashes (Table F-1), injury front-to-rear crashes (Table F-2), and serious front-to-rear crashes (Table F-3).

Table F-1 Fit Statistics for All Front-to-rear Crashes Model

Statistical Model	Deviance	Degrees of Freedom	BIC
Model	681,252	135	683,052
Null (Intercept)	800,876	1	800,889

Table F-2 Fit Statistics for Injury Front-to-rear Crashes Model

Statistical Model	Deviance	Degrees of Freedom	BIC
Model	261,517	135	263,275
Null (Intercept)	320,233	1	320,245

Table F-3 Fit Statistics for Serious Front-to-rear Crashes Model

Statistical Model	Deviance	Degrees of Freedom	BIC
Model	22,968	135	24,710
Null (Intercept)	29,651	1	29,664

PAEB Logistic Regression Models

The model, deviance, degrees of freedom, and BIC statistics are presented below for PAEB logistic regression models for injury single-vehicle road-departure crashes (Table F-4) and serious single-vehicle road-departure crashes (Table F-5).

Table F-4 Fit Statistics for Injury Non-motorist Crashes Model

Statistical Model	Deviance	Degrees of Freedom	BIC
Model	47,991	134	49,715
Null (Intercept)	64,362	1	64,374

Table F-5 Fit Statistics for Serious Non-motorist Crashes Model

Statistical Model	Deviance	Degrees of Freedom	BIC
Model	20,404	130	22,075
Null (Intercept)	24,695	1	24,708

LDW/LKA/LCA Logistic Regression Models

The deviance, degrees of freedom, and BIC statistics are presented below for LDW/LKA/LCA logistic regression models for all single-vehicle road-departure crashes (Table F-6), injury single-vehicle road-departure crashes (Table F-7), and serious single-vehicle road-departure crashes (Table F-8).

Table F-6 Fit Statistics for All Single-vehicle Road-departure Crashes Model

Statistical Model	Deviance	Degrees of Freedom	BIC
Model	241,127	136	242,904
Null (Intercept)	400,949	1	400,962

Table F-7 Fit Statistics for Injury Single-vehicle Road-departure Crashes Model

Statistical Model	Deviance	Degrees of Freedom	BIC
Model	106,655	136	108,417
Null (Intercept)	170,034	1	170,047

Table F-8 Fit Statistics for Serious Single-vehicle Road-departure Crashes Model

Statistical Model	Deviance	Degrees of Freedom	BIC
Model	26,192	136	27,948
Null (Intercept)	40,246	1	40,259

Appendix G. Comparison of PARTS and National Crash Datasets

This appendix compares descriptive statistics of the PARTS dataset against NHTSA's Crash Report Sampling System (CRSS) dataset based on analysis by the USDOT Volpe Center. CRSS is a national sample of police-reported crashes involving all types of motor vehicles, pedestrians, and cyclists. The CRSS data presented in this appendix covers 2016 through 2020 (the most recent available year) and includes crashes without restriction on the number of vehicles involved, with a subject (striking) light vehicle, and with all pre-crash scenarios. The PARTS dataset consists of crashes from January 2016 to August 2021 for 13 states and only consists of the crashes in which at least one vehicle matches the 93 vehicle models between model year 2015 and 2020 contributed by PARTS OEM partners.

In general, the variables studied align well between the PARTS dataset and the CRSS dataset. However, differences exist between the two datasets with respect to specific variables (e.g., age and gender) and how they are standardized or reclassified (see discussion below).

Driver Age

The PARTS dataset has a lower proportion of records with drivers under age 24 than the CRSS dataset, as shown in Figure G-1.

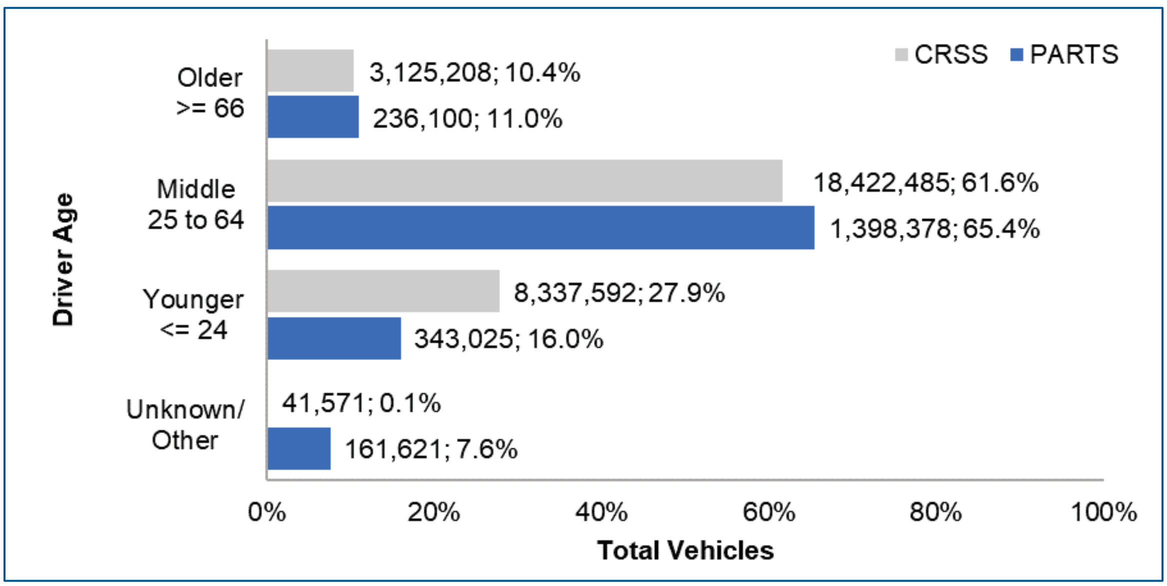


Figure G-1 Comparison of CRSS and PARTS Driver Age (Volpe data field)

Driver Gender

The PARTS dataset has a higher proportion of records with female drivers and a lower proportion of male drivers than the CRSS dataset (see Figure G-2).

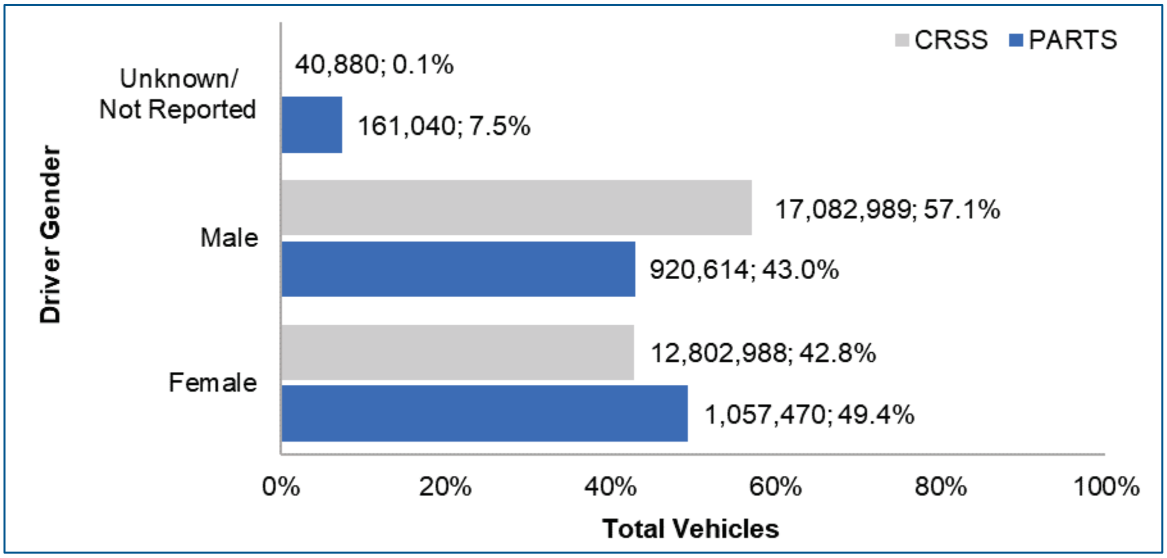


Figure G-2 Comparison of CRSS and PARTS Driver Gender

Driver Impairment

The PARTS dataset has a lower proportion of records where driver impairment was identified (i.e., was yes), as illustrated in Figure G-3. Impairment in the CRSS dataset is a Volpe-defined field that can include impairment due to alcohol, drugs, physical/physiological, etc.

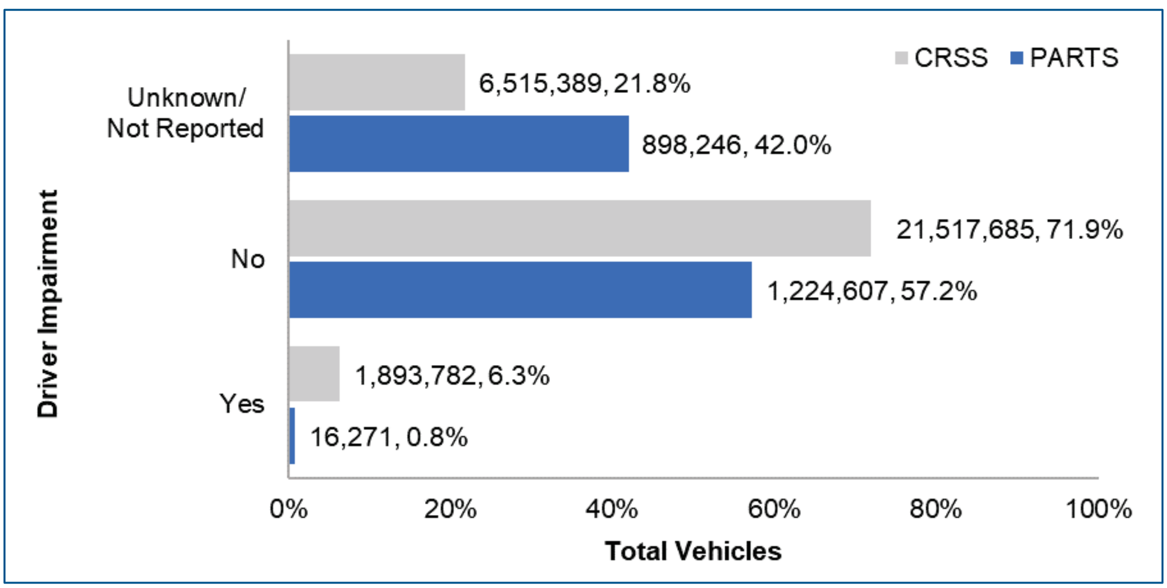


Figure G-3 Comparison of CRSS and PARTS Driver Impairment

Driver Distraction

The PARTS dataset has a lower proportion of records with distracted and unknown/not reported, and a higher proportion with not distracted drivers, than the CRSS dataset (see Figure G-4).

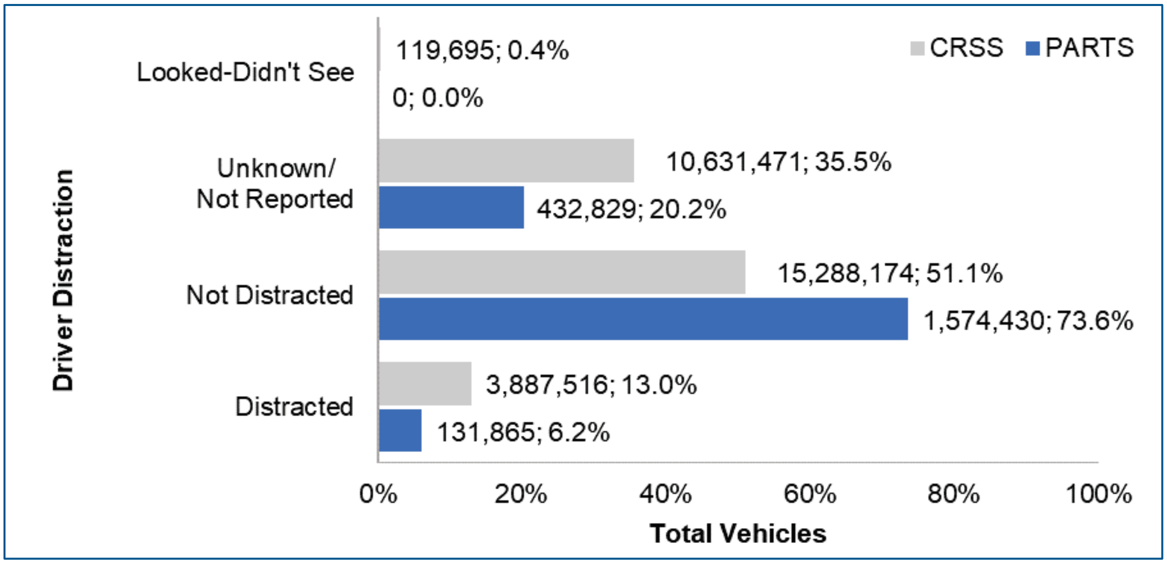


Figure G-4 Comparison of CRSS and PARTS Driver Distraction

Speed Limit

Compared to CRSS, the PARTS dataset has a higher proportion of records with speed limits less than 35 mph and a lower proportion of records with speed limit is unknown (see Figure G-5).

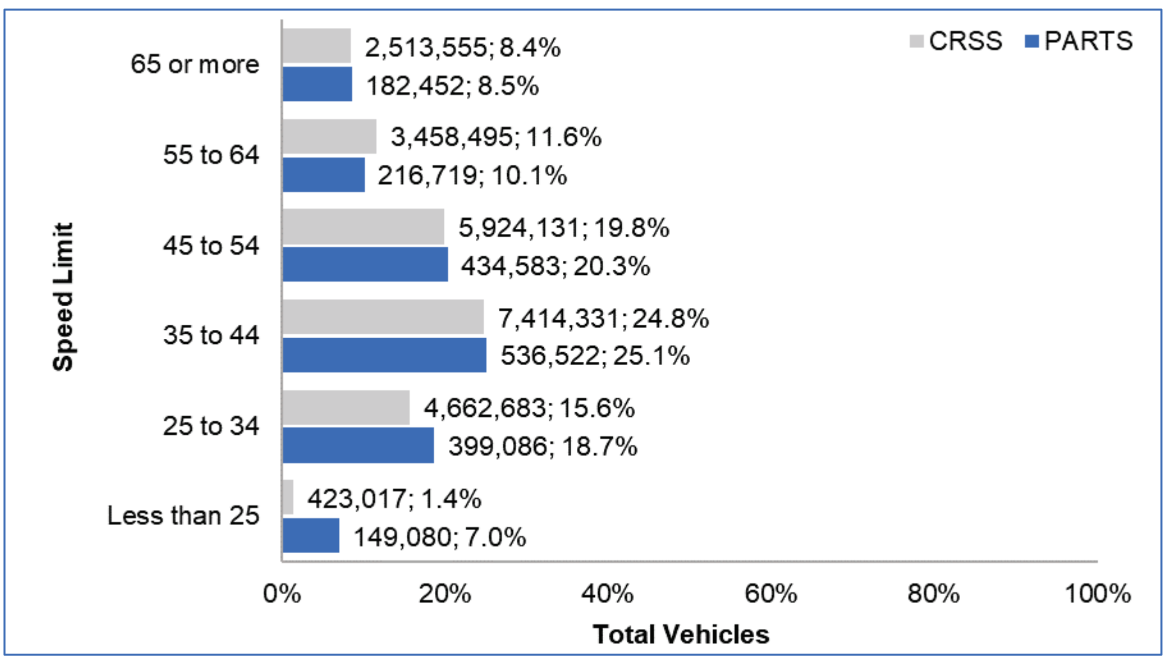


Figure G-5 Comparison of CRSS and PARTS Speed Limit

Roadway Alignment

The PARTS dataset has a higher proportion of records with straight roadway alignment, and a lower proportion with curved or unknown roadway alignment than the CRSS dataset, as shown in Figure G-6.

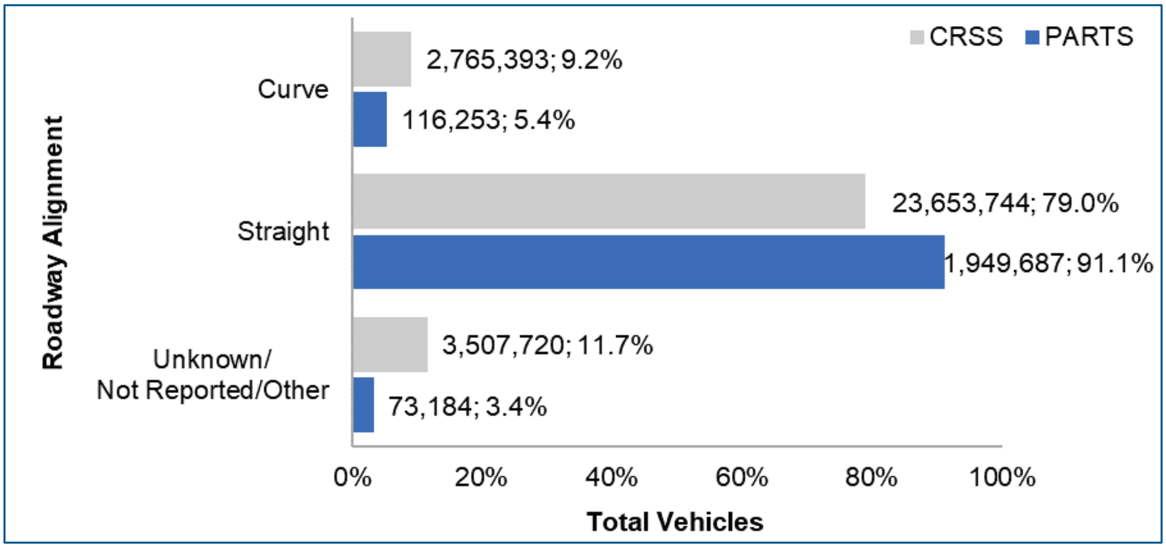


Figure G-6 Comparison of CRSS and PARTS Roadway Alignment

Light Condition

The PARTS dataset has a lower proportion of records with dark not lighted and dark lighted/dawn/dusk conditions, and a higher proportion with other light conditions than CRSS (see Figure G-7). Note that the Volpe query merged two fields, dark lighted and dawn/dusk, and CRSS does not include the dark not lighted condition (Volpe query treated this as dark).

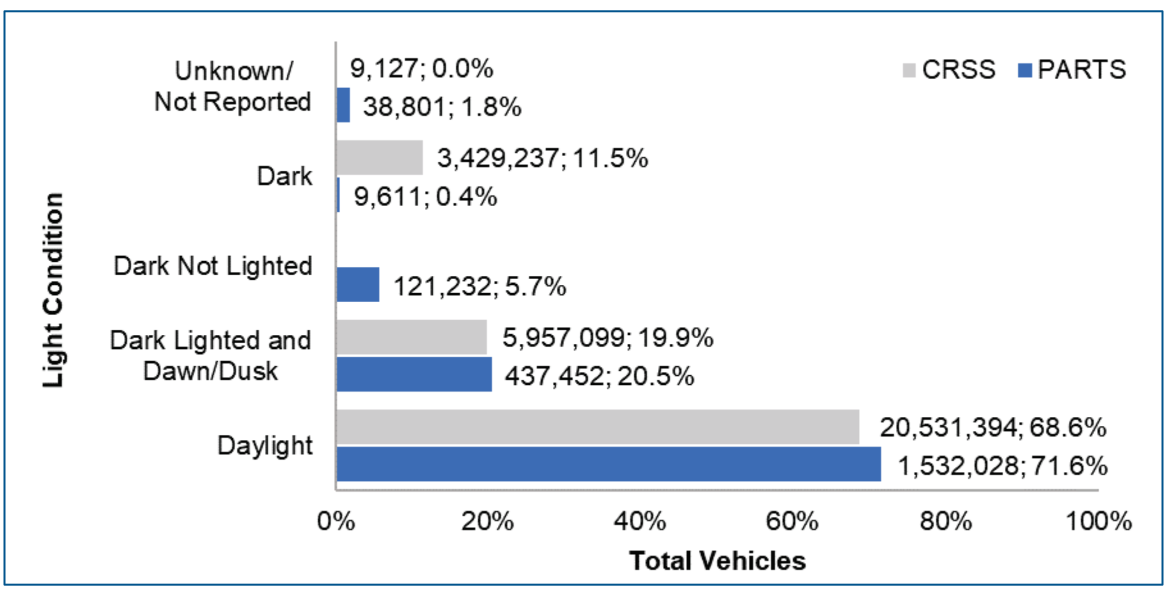


Figure G-7 Comparison of CRSS and PARTS Light Condition

Intersection

The PARTS dataset has a higher proportion of records occurring at non-junctions (non-intersections). PARTS also classifies any intersection-related crashes as intersection, as shown in Figure G-8.

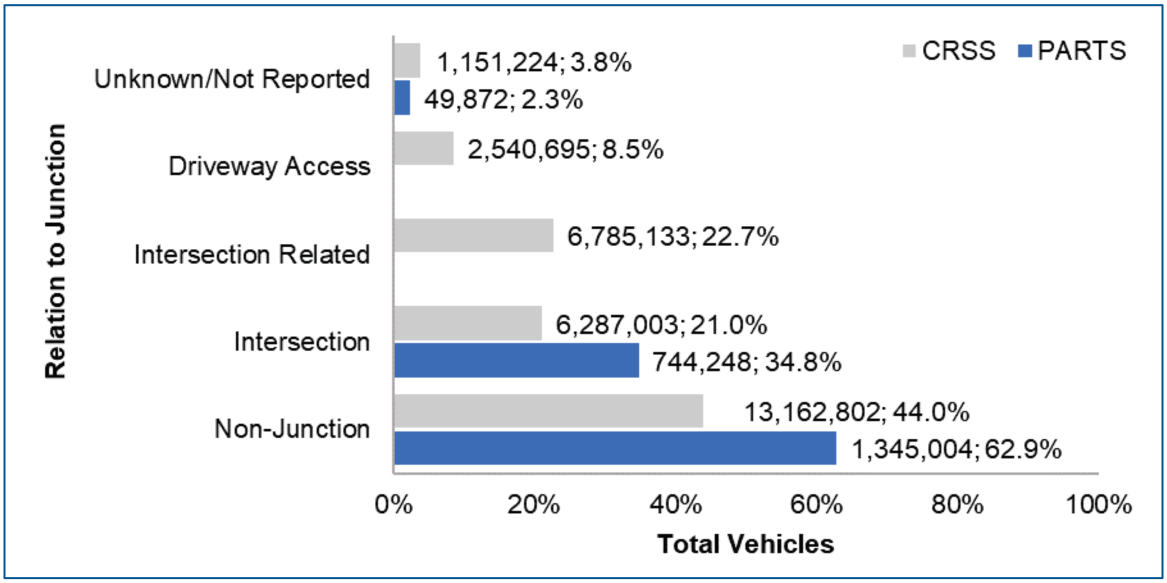


Figure G-8 Comparison of CRSS and PARTS Relation to Junction

Road Surface

The PARTS dataset has a higher proportion of records occurring on dry roads and a lower proportion of records where road surface condition is unknown/not reported than CRSS (see Figure G-9).

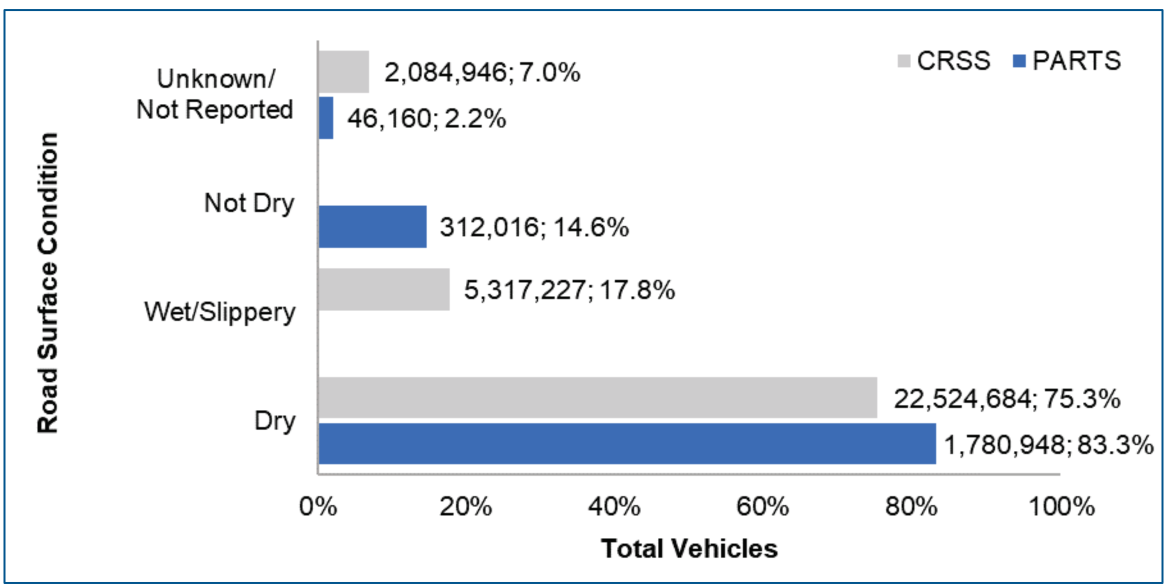


Figure G-9 Comparison of CRSS and PARTS Road Surface Condition

Weather

The PARTS dataset generally aligns with CRSS with regard to weather with perhaps a lower proportion of adverse weather and a higher proportion of records unknown/not reported (see Figure G-10).

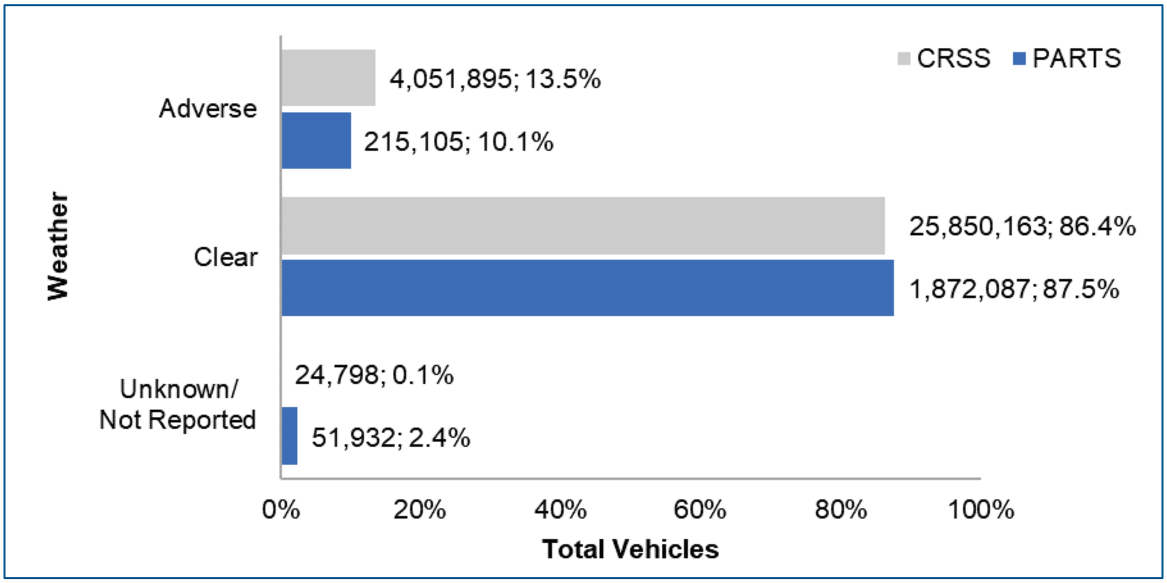


Figure G-10 Comparison of CRSS and PARTS Weather

[End of report]

