REAL-WORLD EFFECTIVENESS OF MODEL YEAR 2015–2020 ADVANCED DRIVER ASSISTANCE SYSTEMS

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ABSTRACT

In 2020, an estimated 2.3 million people were injured in traffic crashes, and 38,824 people were killed on U.S. roadways [1]. Advanced driver assistance systems (ADAS) in passenger 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. To address this need, the Partnership for Analytics Research in Traffic Safety (PARTS) was formed in 2018 as an independent, voluntary data sharing and analysis partnership among eight automobile manufacturers and the United States Department of Transportation (USDOT). The not-for-profit MITRE Corporation (MITRE) operates PARTS as the independent third party and conducted this study at the direction of and in collaboration with the PARTS partners.

The objective of this PARTS study was to explore the real-world effectiveness of ADAS features in reducing system-relevant crashes, specifically front-to-rear crashes for forward collision warning (FCW) and automatic emergency braking (AEB) and single-vehicle road-departure crashes for lane departure warning (LDW), lane keeping assistance (LKA), and lane centering assistance (LCA). This study combined 13 states' police-reported crash data (2016 to 2021) with vehicle equipment data from 47 million vehicles representing 93 vehicle models (model years 2015 to 2020), resulting in the study dataset of 2.4 million crash-involved vehicles. This study defined three crash severities (all, injury, serious) and estimated ADAS effectiveness for each using quasi-induced exposure and logistic regression, comparing vehicles equipped with ADAS against vehicles without those features.

For the population of all front-to-rear crashes, the study estimated that crashes were reduced by 49% (Wald 95% CI: 48 to 50%) when the striking vehicle was equipped with both FCW and AEB compared against striking vehicles that were not equipped with either. For FCW alone, the estimated reduction is 16% (13 to 20%). For the population of front-to-rear crashes involving injury, effectiveness estimates were slightly higher. The study estimated that front-to-rear crashes were reduced by 53% (51 to 54%) when the striking vehicle was equipped with both FCW and AEB. For FCW alone, the estimated reduction for crashes with injuries is 19% (13 to 25%). Altogether, this study shows that the combination of warning and active braking reduced more front-to-rear collisions than warnings alone. The study demonstrates that AEB performs well even when weather and lighting conditions are not ideal. This study investigated the effectiveness of Pedestrian AEB with non-motorists but was unable to detect an effect. For single vehicle road departure crashes, this study estimated that LDW and LKA reduced crashes by 8% (5 to 12%). When adding LCA, crashes are reduced by about the same amount (9%, 4 to 14%). This study did not find significant results for vehicles equipped with LDW alone.

INTRODUCTION

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 ADAS features over time as 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 by enabling collaborative data sharing and analysis among industry and government participants.

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 ADAS and other emerging safety technologies. PARTS partners (see Figure 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

Figure 1. PARTS Partners.

party (ITP) to ensure that partners' interests and sensitive data are protected 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 according to partner direction.

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]. Since the conclusion of this study (see full report [4]), the Ford Motor Company has joined PARTS. 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.

Related Work

In preparation for conducting this study, PARTS conducted a literature review. This review focused on studies in the last 5 years that had comparable research objectives 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) [5] [6] [7] [8] and Impact Research/Toyota [9] [10] have studied the effectiveness of ADAS features but have done so for only a single automobile manufacturer and a more
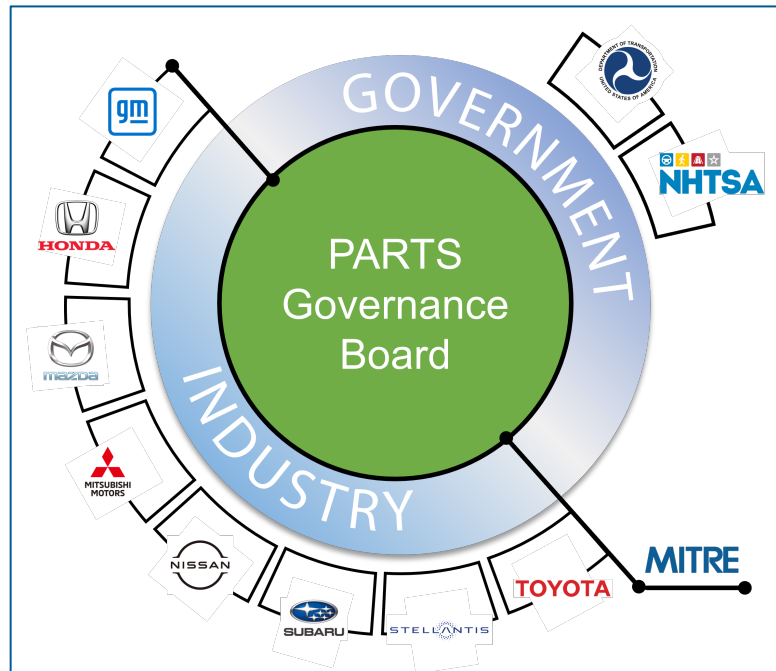
limited sample size. Researchers with the Insurance Institute for Highway Safety (IIHS) [11] [12] [13] have looked at effectiveness of ADAS features across a variety of automobile manufactures but with smaller sample sizes.

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.

DATA AND METHODOLOGY

This PARTS study used real-world data to explore the effectiveness of six ADAS features to reduce system-relevant crashes. The primary research questions were, 1) To what extent do FCW and AEB reduce front-to-rear crashes? and, 2) To what extent do LDW, LKA, and LCA reduce single-vehicle road-departure crashes? A goal was also to determine if a given ADAS feature's effectiveness changed under different conditions (e.g., dark 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. Please see the full report for more detail [4].

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. Injury types are based on KABCO scores using a nested 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) [14] 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.

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.

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

Figure 2. Nested Injury Structure.

Data Overview

This PARTS study used two primary data sources: OEM-provided vehicle data on vehicles for select makes/models for 2015–2020 model years, at the Vehicle Identification Number (VIN) level; and NHTSA-provided police-reported crash data for select states during 2016–2021, at the 17-digit VIN level.

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). The data included 93 models from model years 2015–2020 and covered seven vehicle segments noted below.
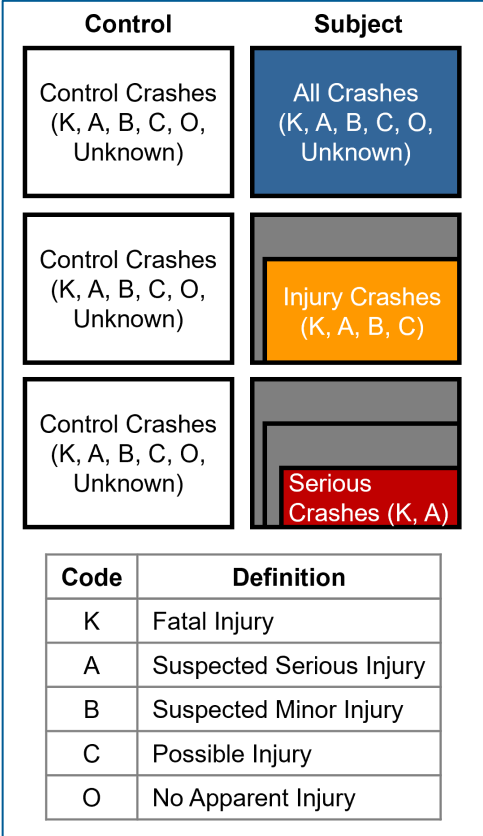
- **Small Car (14):** Acura ILX, Honda Civic, Fit, & Insight; Mazda3 sedan & hatchback; Nissan Versa & Sentra; Subaru Impreza, WRX, & Crosstrek; Toyota Corolla, Prius, & C-HR.

- **Midsize Car (13):** Buick Regal & Chevrolet Malibu; Acura TLX, Honda Accord; Mazda6; Nissan Altima & Maxima; Alfa Romeo Giulia, Chrysler 200; Subaru Legacy & Outback; Lexus IS, Toyota Camry.

- **Large Car (8):** Buick LaCrosse, Chevrolet Impala; Chrysler 300, Dodge Charger & Challenger; Lexus ES & LS, Toyota Avalon.

- **Small SUV (19):** Buick Envision, Chevrolet Equinox, & GMC Terrain; Acura RDX, Honda HR-V & CR-V; Mazda CX3, CX5, & CX-30; Mitsubishi Outlander Sport & Eclipse Cross; Nissan Rogue; Fiat 500X, Jeep Compass, Renegade, & Wrangler 2DR; Subaru Forester; Lexus NX, Toyota RAV4.

- **Midsize SUV (22):** Buick Enclave, Chevrolet Traverse, Cadillac SRX & XT5, GMC Acadia; Acura MDX, Honda Pilot & Passport; Mazda CX-9; Mitsubishi Outlander; Nissan Murano, Pathfinder; Alfa Romeo Stelvio, Dodge Durango, Jeep Cherokee, Grand Cherokee, & Wrangler Unlimited; Subaru Ascent; Lexus RX & GX, Toyota Highlander & 4Runner.

- **Pick-Up and Large SUV (14):** Chevrolet Tahoe/GMC Yukon, GMC Sierra 1500; Honda Ridgeline; Nissan Armada, Titan, & Frontier; Ram 1500, Ram 2500, Ram 3500, Jeep Gladiator; Toyota Tundra, Tacoma, & Sequoia.

- **Minivan (3):** Honda Odyssey; Chrysler Pacifica; Toyota Sienna.

PARTS selected the models above based on the following guidelines: (1) 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; (2) At least one model year for each model was required to have at least one ADAS feature in scope for the analysis; (3) 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.

Crash Data was 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 used crashes that occurred between January 2016 and August 2021 for the 13 states included in the analysis (see Table 1). While other states (California, Illinois, Kansas, Maine, Nebraska, Washington) 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.

Table 1.
Crash Data by State and Time Period Covered

State (Acronym)	Start Date	End Date	State (Acronym)	Start Date	End Date
Arkansas (AR)	1/1/2016	8/2/2021	Ohio (OH)	1/1/2019*	7/31/2021
Connecticut (CT)	1/1/2016	7/30/2021	Tennessee (TN)	1/1/2018*	8/1/2021
Florida (FL)	1/1/2016	8/1/2021	Texas (TX)	1/1/2018*	8/2/2021
Indiana (IN)	1/1/2016	7/28/2021	Utah (UT)	1/1/2017*	8/2/2021
Iowa (IA)	1/1/2017*	8/1/2021	Virginia (VA)	1/1/2016	8/2/2021
Maryland (MD)	1/1/2016	8/3/2021	Wisconsin (WI)	1/1/2018*	8/2/2021
Nevada (NV)	1/2/2018*	8/3/2021			

* Asterisks indicate meaningfully different start dates

Some limitations of police-reported crash reports are important to understand as a basis for interpreting results. KABCO [14], 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 [15] [16] [17] [18]. 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.

Methodology – System-Relevant Crashes and Control (Exposure) Crashes

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.

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.

<u>**Control crashes**</u> were defined for analysis of all ADAS features as the 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.

- 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).

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

<u>**Front-to-rear crashes**</u>, which are FCW/AEB system-relevant, were defined 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).

<u>**Single-vehicle road-departure crashes**</u>, which are LKA/LDW/LCA system-relevant, were defined 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.

Methodology – 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

Figure 3. Joining Crash Data and Vehicle Data.

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 **Error! Reference source not found.**).
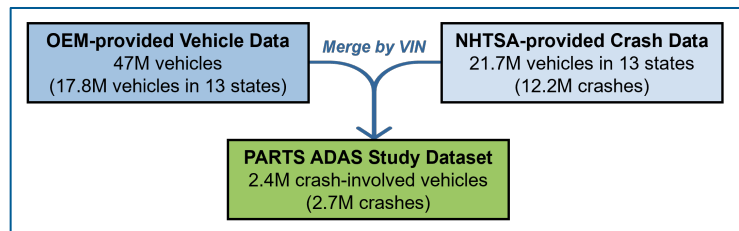
PARTS deleted observations from the study dataset if they were missing any of the variables expected for the logistic regression. These deleted observations represented about 10% of the data.

Methodology – 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 [7]. 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. This method of quasi-induced exposure has been widely used when studying ADAS feature effectiveness. IIHS [19], Impact Research/Toyota [9], and UMTRI [8] (which has a particularly accessible explanation of quasi-induced exposure) have all used quasi-induced exposure to study ADAS feature effectiveness.

Methodology – Logistic Regression Model Design

PARTS used logistic regression to estimate the effectiveness of sets of ADAS features in reducing relevant crashes 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). PARTS set the binary outcome variable of the logistic regression as system-

relevant crashes (coded as 1) and control crashes (coded as 0). PARTS included sets of ADAS features as an explanatory variable to enable estimates of effectiveness.

To measure the uncertainty of the estimates, PARTS calculated Wald confidence intervals (CIs) at the alpha = 0.05 level for the coefficients. To formulate ADAS effectiveness more intuitively, where a higher value indicates more effectiveness, PARTS calculated the percentage reduction of equipped vehicles odds compared to unequipped vehicles odds.

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). PARTS transformed continuous variables into categorical variables, which effectively allows for non-linear relationships. Table 2 describes the driver, vehicle, environmental, and crash-related covariates PARTS identified for the logistic regression models.

Table 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 above	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.

Variable	Explanation	Specification in Logistic Regression	Additional Notes
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

Covariates as Main Effects were selected by PARTS within the logistic regression models 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. 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 [20]. 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.

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. PARTS included blind spot warning (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.

Covariates as Interactions were included given 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. 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 could be due to confounding factors rather than the actual interacted variables. Additionally, the interactions, and effectiveness in general, could be influenced by incorrect specification of the model. Evidence exists that single-vehicle road-departure and non-motorist logistic regressions are more sensitive to incorrect specification than front-to-rear. Please see the full report [4] for more details on methodology.

RESULTS

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.

Overall FCW/AEB results are that vehicles equipped with FCW + AEB showed a substantial crash reduction of about half, as shown in Figure 4 (associated sample sizes are shown in the data table).
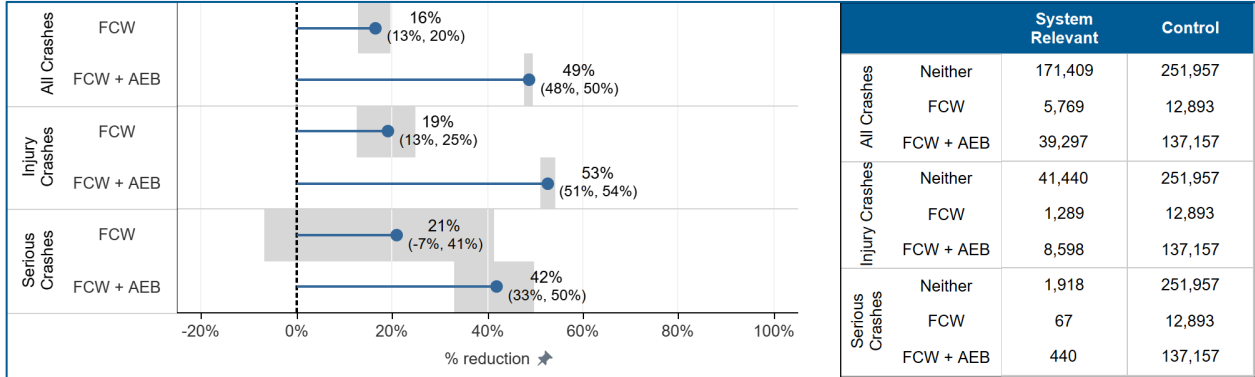

		System Relevant	Control
All Crashes	Neither	171,409	251,957
	FCW	5,769	12,893
	FCW + AEB	39,297	137,157
Injury Crashes	Neither	41,440	251,957
	FCW	1,289	12,893
	FCW + AEB	8,598	137,157
Serious Crashes	Neither	1,918	251,957
	FCW	67	12,893
	FCW + AEB	440	137,157

Figure 4. Results for FCW/AEB and Associated Sample Sizes.

FCW/AEB results for all crashes show 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, 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.

FCW/AEB results for injury crashes were based on a dataset that was about 20% of the total system-relevant crashes, as shown in Figure 4. 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.

FCW/AEB results for serious crashes were based on 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. 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. The FCW case resulted in a CI that covered zero reduction in crashes (i.e., may not necessarily be effective).

FCW/AEB results by condition were generally effective even in poor conditions. 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 **Error! Reference source not found.**) 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. 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.

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.
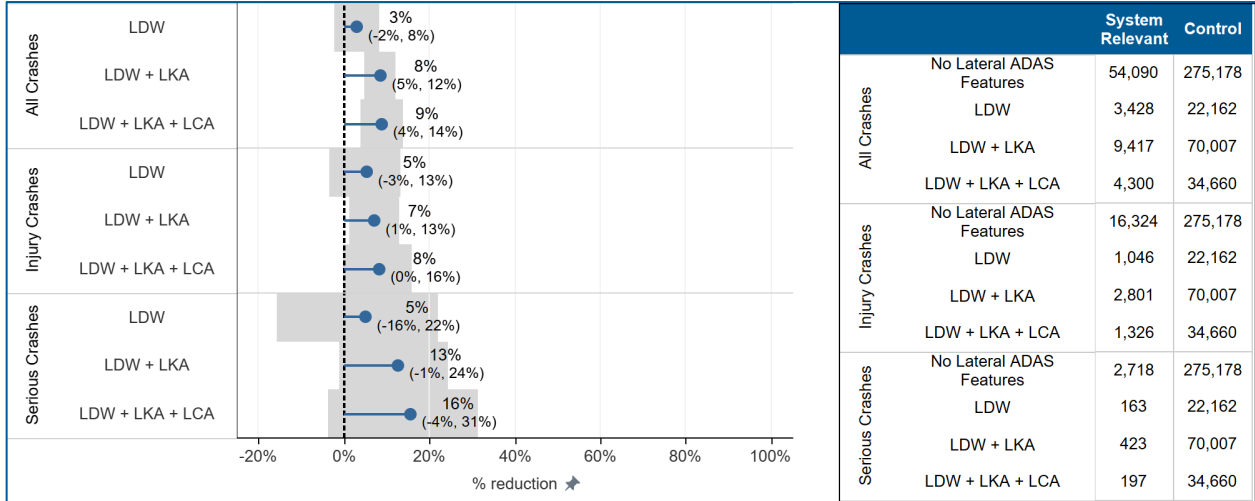

Figure 5. Results for LDW/LKA/LCA and Associated Sample Sizes.

Overall LDW/LKA/LCA results are that 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 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.

LDW/LKA/LCA results for all crashes are that 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 [21] [22].

LDW/LKA/LCA results for injury crashes are based on reduced sample sizes (by about 70%) as shown in see Figure 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.

LDW/LKA/LCA results for serious crashes are based on about 5% of the total system-relevant crashes (see Figure 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.

LDW/LKA/LCA results by condition did not find 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.

DISCUSSION

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.

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 [23]. Because drivers likely have FCW + AEB enabled at high rates [24] compared with other ADAS features, these estimates show the real-world effectiveness of AEB as a safety technology.

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, 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 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 several 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 operational design domains for ADAS features 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.

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.

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 [24] – 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 nuisance, 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.

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.

STUDY LIMITATIONS

This study:

1. 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.

2. 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.

3. 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.

4. Uses police-reported crash reports as a primary source of data, which presents a series of well-known challenges. KABCO [14], 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 [15] [16] [17] [18]. 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.

5. Has results that 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. 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).

SUGGESTIONS FOR FUTURE RESEARCH

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. 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). Understanding the trajectories of vehicles and pedestrians prior to a collision is essential for understanding crash outcomes. 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.

In future iterations, PARTS will seek to incorporate more vehicle equipment data from its OEM partners, including from its newest partner (Ford). 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. PARTS will integrate additional police-reported crash data, from more states, to expand the sample sizes and increase the representativeness of the study. As sample sizes increase, especially for injury and serious crashes, it is expected that uncertainty in the estimates will decrease, 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.

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