Advanced Driver Assistance System Crash Rate Assessment Using Vehicle-Specific Mileage Data

June 2025

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

Acknowledgments

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1 Executive Summary

This study explores the use of Vehicle Miles Traveled (VMT) data in evaluating the effectiveness of Advanced Driver Assistance Systems (ADAS). Leveraging a large dataset pooled from multiple vehicle manufacturers participating in a collaboration between government and industry, this study provides more comprehensive coverage than other sources, demonstrating the feasibility of conducting robust safety analyses using vehicle-level mileage data to control for exposure.

VMT data included a combination of telemetry-based and dealer-visit based collection methods. Despite variability in manufacturer reporting practices and changes over time, the pooled VMT data produced ADAS effectiveness results consistent with previous studies, demonstrating its potential value to traffic safety research. The findings underscore the importance of establishing standardized reporting protocols to enhance the utility of pooled datasets. Cumulative measures, such as year-end mileage, offer significant advantages by simplifying data management and mitigating issues like corrupted or missing data.

The study also reveals that while more frequent data reporting improves accuracy, estimates remain reliable even with time gaps of several months. Aggregated measures, such as annual or monthly mileage per vehicle, are sufficient for certain types of safety analyses, offering a balance between efficiency and data quality. This approach avoids the complexity and volume of sensitive trip-level data while maintaining analytical effectiveness.

A key contribution of this research is the validation of Quasi-Induced Exposure (QIE) for conducting ADAS effectiveness analyses. Using VMT as an exposure metric, rear-end struck vehicle crash rates were assessed for vehicles with and without Automatic Emergency Braking (AEB) equipment. The findings suggest that AEB equipage is associated with reduced or neutral rear-end struck rates, supporting the use of QIE in analyzing ADAS effectiveness.

In conclusion, this study demonstrates the potential of pooled VMT data to advance traffic safety research. The insights gained here can guide future efforts to standardize reporting practices, optimize data aggregation methods, and leverage telematic data sources for more effective safety analyses and interventions.

2 Introduction

ADAS hold significant promise for enhancing road safety by reducing crashes, preventing serious injuries, and potentially saving thousands of lives annually. The Partnership for Analytics Research in Traffic Safety (PARTS), depicted in Figure 1, was established in 2018 as a public-private partnership between several automobile manufacturers and the National Highway Traffic Safety Administration (NHTSA), and operated by The MITRE Corporation (MITRE) as an independent third party. The goal of PARTS is to advance traffic safety through the collaborative analysis of automotive safety, with partners voluntarily sharing data for joint analyses.

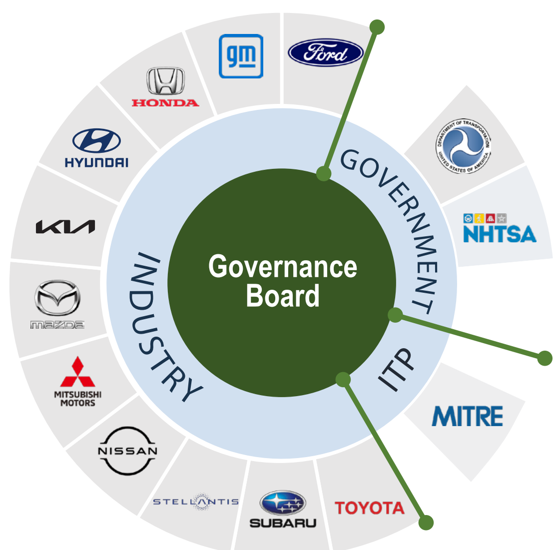

Figure 1. PARTS Participation

PARTS has successfully leveraged shared data to measure real-world effectiveness of ADAS technologies [1] [2]. Prior PARTS studies and similar work by others [1] [2] [3] rely on QIE methods to account for vehicle exposure, a critical factor in quantifying vehicle safety performance. This study aims to validate these methods. PARTS undertook an effort to integrate VMT data from dealer visits and telematics sources with vehicle equipage information, all provided by automakers, and police-reported crash data, provided by NHTSA. This enriched dataset offers a comprehensive and diverse perspective on the relationship between miles traveled and crash occurrences—insights that would be challenging to achieve without a collaborative effort like PARTS. This study also demonstrates the potential of using pooled telematics data to explore critical safety factors, such as the usage and activation rates of ADAS, thereby contributing to more informed and effective traffic safety strategies.

This ADAS crash rate study serves as a proof of concept for applying vehicle-specific exposure data to the study of ADAS effectiveness, specifically VMT. In addition to illustrating the potential for future work in this space, the goal of the study was to validate prior findings from QIE analyses performed by the PARTS partnership.

Study Overview

VMT is commonly understood, relatively straightforward to calculate, and serves as a valuable exposure measure in traffic safety research. Use of field-based VMT has not been widely cited in the literature, and availability of vehicle-level VMT varies across research groups.

The study began with a limited set of vehicle models and allowed for data collection from either telematics or dealer visit sources to facilitate initial progress. The data collection phase demonstrated the feasibility of sharing limited sets of raw telematics data, which is vehicle-based data collected through telecommunication services during operation of the vehicle, stored in databases and managed by the automaker. The process of ingesting and standardizing data provided valuable insights into the variety of data formats, data completeness, and data quality. For example, gaps in data reporting across vehicles resulted in eliminating a number of Vehicle Identification Numbers (VIN) that had no VMT reported. While future studies may consider augmenting data through mileage estimation, in the current effort the partnership opted to sacrifice some vehicles to improve accuracy. For this study, partner-provided data were used to estimate each vehicle's VMT at the end of each calendar year. This approach allowed for a consistent temporal framework for analysis. The team then calculated crash rates using this VMT exposure metric and compared the results to those obtained from a QIE analysis conducted as part of this study.

3 Literature Review

As ADAS features have become widespread in U.S. vehicles over the past 10 years [4], there has been increased interest in measuring their effect on traffic safety. Researchers attempting to fill the gap in understanding ADAS effectiveness have leveraged a variety of methods and data sources. A common concern in such studies is how to properly account for exposure. In this section, we describe a number of approaches used and highlight how they relate to the current PARTS analysis.

Vehicle Mileage and Crash Rates

Cicchino's 2024 study examines crash rates in vehicles with ADAS [5]. Utilizing aggregate VMT data from Carfax, Cicchino compares crash rates across various ADAS features, including AEB, Forward Collision Warning (FCW), Adaptive Cruise Control (ACC), Lane Keeping Assistance (LKA), and Lane Departure Warning (LDW). While Cicchino's study provides useful insights, it uses average VMT by category rather than VIN-specific mileage. The dataset from the PARTS data-sharing partnership, with its large set of VIN-specific VMT data, enables more granular investigations into how specific ADAS features influence crash rates.

Elvik's 2023 synthesis of driver mileage and accident involvement highlights the limited number of studies examining the relationship between mileage and crash involvement [6]. Elvik points out the inaccuracies of self-reported data and the need for high-quality data to control for variable factors such as sex and driving environment. The synthesis suggests crash involvement is not a linear function of annual miles driven, underscoring the value of vehicle-specific mileage information. Such detailed data facilitate the development of models that can better assess the safety impacts of ADAS. Elvik's concerns about self-reported data are addressed in PARTS through the use of a large, automatically recorded dataset with vehicle-specific information, but it does lack information on confounding factors such as driver age and sex associated with mileage accumulation.

Naturalistic Driving Studies and Crash Data

Flannagan et al.'s 2023 study on establishing a crash rate benchmark using large-scale naturalistic human ride-hail data provides insights into crash rates in urban environments [3]. Conducted in San Francisco with a fleet of fewer than 1,500 vehicles, the study reports a crash rate of 64.9 crashes per million Operational Design Domain (ODD) miles. ODD miles are related to VMT, but restricted to a defined subset of driving, so crash rates are not directly comparable. This research underscores the importance of understanding driving context when measuring real-world crash rates, including driver-, trip-, and geography-related factors. In this case, the vehicles were operated largely by young male rideshare drivers. While this type of data collection has the potential to provide a very detailed analysis of many aspects of driving, it requires expensive data collection, reduction, and analysis that is inaccessible to most researchers and often involves limited fleets of volunteer drivers. Kusano et al.'s 2024 comparison of Waymo rider-only crash data to human benchmarks offers an analysis of Automated Driving System (ADS) crash data [7]. Using NHTSA's Standing General Order reporting and adjusting for underreporting biases, the study provides a comparison of ADS and human-driven crash rates. The research highlights the challenges of working with public crash and VMT data, emphasizing the need for accurate datasets to evaluate the safety performance of ADS, especially when ADS vehicles have limited ODDs and crash reporting thresholds differ from typical human-driven vehicles. Although the PARTS dataset does not currently include ADS, future analyses of systems with disparate ODDs will face similar challenges.

4 Data Sources and Preparation

Data Overview

This PARTS study used three primary data sources:

- Vehicle VMT data: collected at dealer visits and/or via telematics
- Vehicle equipage data
- Crash data.

The nine PARTS auto manufacturer partners contributed VIN-specific VMT data for 8.6 million vehicles, yielding a substantially larger vehicle set than used by any of the related studies identified in the literature review. Data were collected in two ways: during dealer visits and via telematics. Dealer-based VMT records provided odometer readings reported during visits for vehicle service, as well as information on the service date and the state where the visit occurred. Telematics records included odometer readings reported by the vehicle in response to an established trigger or at some regular interval determined by the manufacturer as well as the date reported. Two manufacturers provided both telematics and dealer-based data, three provided telematics only, and four provided dealer visit data only. Each partner provided mileage data for two U.S.-sold models, one from the small Sport Utility Vehicle (SUV) segment and one pickup truck, for model years 2018 to 2023. All records included model, model year, timestamp, VMT, and in some cases state.

Vehicle equipage data came from the 2025 PARTS ADAS Effectiveness Study [1]. Auto manufacturer partners provided VIN-specific vehicle equipment data for approximately 98 million passenger vehicles sold in the United States, including 168 vehicle models from model years 2015–2023 and covering 10 vehicle segments (see Figure 2). This vehicle equipment data enabled the identification of the following ADAS features present on the vehicle at the time of manufacture[1]: AEB, pedestrian AEB, LDW, LKA, and Lane Centering Assistance (LCA).

[1] The availability or activation of ADAS features at the time of crash was not considered for this study.

Original Equipment Manufacturer (OEM)

	FORD	GM	HONDA	HYUNDAI	MAZDA	MITSUBISHI	STELLANTIS	SUBARU	TOYOTA	Total
Small Car	Fiesta Focus	ATS, CT4, Cruze, Volt, Bolt EV, Sonic, Spark	ILX (Integra) Civic, Fit, Insight	Accent Veloster	Mazda3-4Dr & HB	Mirage Mirage G4		Impreza WRX Crosstrek BRZ /GT86	Corolla 4Dr & HB, Prius, C-HR	27
Midsize Car	MKZ Fusion Mustang	Malibu Regal Verano CTS	TLX Accord	Elantra G70 Ioniq 6	Mazda6		Alfa Romeo Giulia Chrysler 200	Legacy Outback	Camry Lexus IS	19
Large Car	Taurus Continental MKS	Impala LaCrosse CT5, CT6, XTS		G80 G90 Sonata			Chrysler 300 Charger Challenger		Avalon ES LS Crown	18
Small SUV	EcoSport, Escape, Corsair, MKC, Bronco Sport	Equinox, Terrain, Envision, Encore, Encore GX, XT4, Trailblazer, TRAX	RDX HR-V CR-V	GV60, Ioniq Kona Tuscon, Venue	CX-3, CX-5, CX-30, CX-50 MX-30 (EV)	Outlander Sport Eclipse Cross	Renegade Compass Wrangler 2DR	Forester	RAV4, NX, Venza, Corolla Cross UX	37
Midsize SUV	Bronco, Edge Explorer, Nautilus, Aviator, Mustang Mach-E (EV)	Acadia, Enclave, Traverse, SRX, XT5, XT6, Blazer, Lyriq (EV)	MDX Pilot Passport	GV70 GV80 Palisade Sante Fe	CX-9	Outlander Outlander PHEV	Durango, Cherokee, Grand Cherokee, Stelvio, Wrangler 4DR	Ascent	Highlander RX, 4Runner, GX BZ4X/Solterra (EV)	35
Large SUV	Expedition Navigator	Tahoe, Yukon Yukon XL Suburban Escalade					Wagoneer Grand Wagoneer		Sequoia	10
Medium Pick-Up	Maverick Ranger	Colorado Canyon	Ridgeline	Santa Cruz			Jeep Gladiator		Tacoma	8
Light Duty Pick-Up	F-150 F-150 Lightning (EV)	Sierra LD Silverado LD					Ram 1500		Tundra	6
Heavy Duty Pick-Up	F-250 (Super Duty)	Sierra HD Silverado HD Hummer (EV)					Ram 2500			5
Minivan			Odyssey				Pacifica		Sienna	3
	26	44	14	18	9	6	19	8	24	168

Figure 2. Vehicle Data: Mapping Models to Segments

The 2025 PARTS study also used police-reported crash data from 16 states. Data from 15 of these states was provided by NHTSA through its Consolidated State Crash (CSC) database, which consolidates police-reported crashes received from states through the Electronic Data Transfer (EDT) process. In addition to the CSC data, Michigan crash data were provided by the University of Michigan Transportation Research Institute (UMTRI) with permission from the Michigan State Police. The data used in each case was a census of all police-reported crashes in those states. Data were limited by what was available in the original state-level crash report, and specific fields and data elements varied by state. This study focused on crashes that occurred prior to September 2023, with some variation of data availability across the 16 states included in the analysis. The crash data encompassed a total of 21.2 million crashes involving 36.8 million vehicles.

MITRE linked VMT and vehicle equipage with police-reported crash data, resulting in 279,993 crash-involved vehicles with associated VMT data. These nearly 300,000 vehicles have VMT data, equipage information, and crash data, which allowed for this study of VMT as an exposure metric for ADAS effectiveness.

Data Preparation

In conducting this study, a rigorous data processing protocol for manufacturer VMT records ensured data quality, consistency, and usability. The steps described below also ensured the integrity and confidentiality of the vehicle data.

Data files were first assessed for completeness and accuracy. Minimum required fields included Model, Model Year, VIN, Mileage Read Date, and Vehicle Mileage. Each manufacturer's data adhered to its own reporting conventions, which meant field names, data formats, and mileage read intervals varied. Some manufacturers provided event-driven mileage readings, while others reported data at regular intervals. Each manufacturer's raw files were consolidated into a single file, verifying consistency between raw files and facilitating further processing.

VINs were masked and replaced with unique and persistent identifiers across all datasets as linking values. Records with invalid VINs were excluded during this step to maintain data integrity.

A source field identified records as coming from telematics or dealer visit data.

Data fields were standardized to ensure consistency across manufacturers. This included renaming fields to common names, ensuring uniform data types (e.g., numeric, date-time), converting distance units (e.g., kilometers to miles), and standardizing date formats. Basic filters were also applied to exclude invalid or extreme data points, ensuring mileage values were non-negative, monotonically increasing, and within a reasonable range.

Next, VMT records were linked with PARTS vehicle build data using the masked vehicle identifiers. This step added key vehicle attributes, particularly information about ADAS features, and served to exclude any non-U.S. VMT records received. Additionally, customer state or state of sale was added from the build data in cases where it was not available from the VMT data. The state field was used when merging VMT data with crash data to infer which vehicles were operating in states with available crash data.

The analysis used each vehicle's mileage at the end of each calendar year during the study period. Some manufacturers provided VMT on these dates, but most did not. Therefore, VMT on those key dates required estimation. To be eligible for VMT estimation, vehicles were required to have at least one valid VMT record 30 days or more after sale and to be associated with one of the states with PARTS crash data: Arkansas, Connecticut, Florida, Indiana, Iowa, Kansas, Maryland, Michigan, Minnesota, Nevada, Ohio, Tennessee, Texas, Utah, Virginia, and Wisconsin.

For each combination of vehicle and key date, mileage was estimated using one of the following three methods (in descending order preference):

- Interpolate Pre/Post: Required a VMT update both prior to and within two years after the key date. Key date VMT was estimated using linear interpolation between these reported dates.

- Interpolate Post: If a VMT update was available only within two years after the key date, the customer delivery date was treated as a proxy report with zero mileage, and linear interpolation was performed on that basis.
- Extrapolate: If a VMT report was available only before the key date, average miles per day since customer delivery was computed and used to extrapolate to the key date. This method involves higher estimation error than interpolation. As a partial mitigation, VMT reports greater than one year prior to the key date were excluded.

If none of these methods could be applied, no VMT was estimated. Once mileage estimates at key dates were complete, VIN coverage was assessed across original equipment manufacturers (OEM), vehicle models, and model years to ensure reasonable representation. This included a review of differences in data reporting among OEMs and an examination of how reporting practices evolved over time. Notably, we observed variation in update frequency and vehicle coverage, with a recent shift from dealer-based data to telematics data for those who provided both. Readers are cautioned to bear this variation in mind while interpreting results. Finally, we assessed the estimation error associated with each method, considering the data time interval, and derived insights into the optimal update frequency for maintaining data accuracy.

Descriptive Statistics of the VMT Dataset

The 8.6 million VINs with VMT data accounted for 71% of vehicles with the target models/model years based on PARTS equipage data. Figure 3 shows the counts of crash-involved vehicles with and without VMT data for each model year. Overall counts are greater for earlier model years, largely reflecting greater exposure. The proportion of crash-involved vehicles is greater for more recent model years.

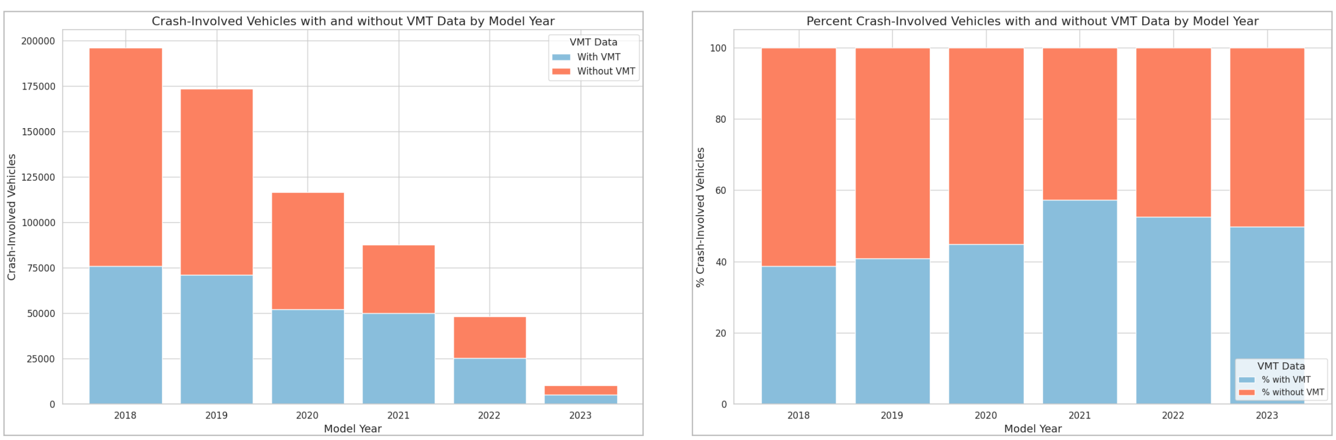

Figure 3. VMT VIN Coverage by Model Year

In terms of data sources, 38% of VINs with VMT were based on telematics data and 68% on dealer visit data; the sum is greater than 100% because some VINs had data from both sources. Most manufacturers provided a sample of observations rather than a complete set of VMT records.

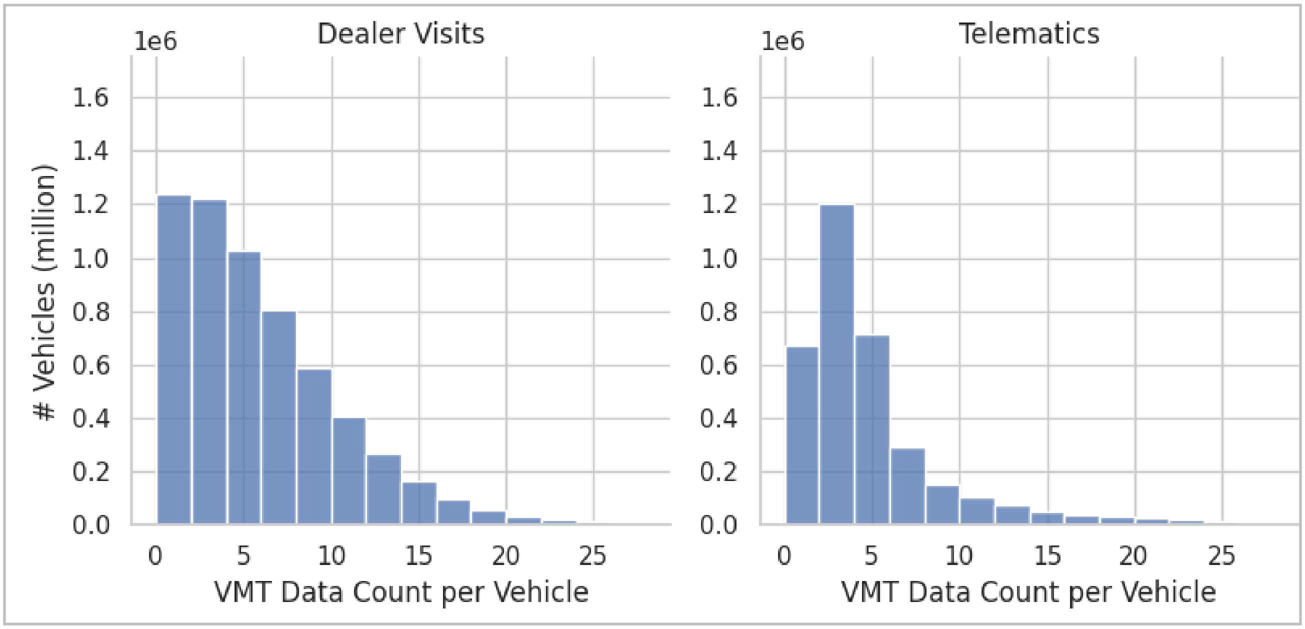

Figure 4 Distribution of VMT Updates per Vehicle

As Figure 4 illustrates, most VINs had between one and 15 VMT updates provided. The frequency of both dealer visits and telematics updates drops as vehicles age; a review of the data indicated the drop-off is gradual.

There were 632,497 crash-involved vehicles from the selected models, model years, and states with associated equipage data. Of these, 279,993 vehicles—or 44.4% of the total—had usable VMT data.

As a validation check, a naïve crash rate was computed from the quotient of crash-involved vehicles with VMT divided by total estimated VMT and compared to NHTSA national crash statistics. The naïve crashed vehicles rate was 2.17 crashed vehicles per million vehicle miles versus 3.46 crashed vehicles per million miles, which was calculated based on NHTSA crash statistics from 2021 [8]. The difference in rates could be related to inaccuracies in aggregate data or other factors that affect mileage driven such as driver demographics, vehicle type, or vehicle age.

Estimation errors are likely higher when there is a larger time gap between recorded and estimated VMT. We assessed estimation error using VINs having at least three VMT updates by excluding a known VMT date, estimating the VMT using each of the methods, and calculating the resulting estimation errors.

Results for each of the three methods are shown in Figure 5. The dark central line is the median error, and the gray bands capture the Inter-Quartile Range (IQR). Errors are much larger for extrapolation than interpolation; extrapolation mileage is also biased on the high side. Based on these patterns, the maximum allowable time gap for estimating VMT was set as two years for interpolation and one year for extrapolation. The irregular pattern of errors from interpolation reflects heterogenous reporting from different partners as well as changing reporting practices over time.

The error patterns suggest recording vehicle mileage at low frequencies, such as quarterly or yearly, may be adequate for many types of analysis. Interpolation errors increase slowly as a function of time gap and are generally less than 500 miles even with a two-year gap, equivalent to less than 5% of typical annual mileage.

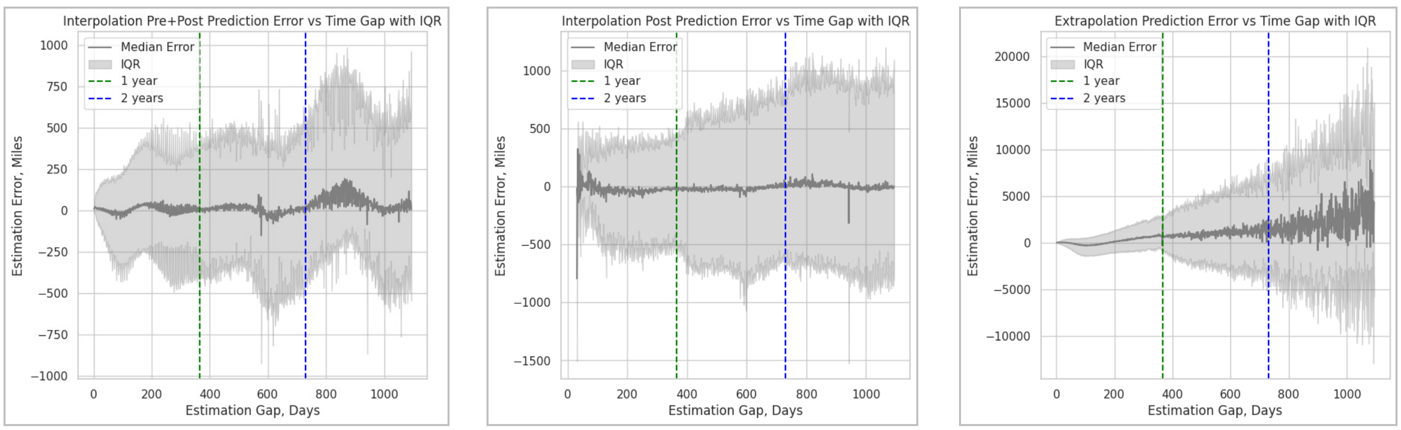

Figure 5. Estimation Error vs. Estimation Type

Methodology Overview

To study the use of VMT as an exposure metric for ADAS effectiveness, we considered system-relevant crash rates. Specifically, we studied the effectiveness of AEB on front-to-rear crashes and Active Lateral (LDW + LKA or LDW + LKA + LCA) systems on Single Vehicle Road Departure (SVRD) crashes. For AEB, we studied two cases: first, where a PARTS vehicle was the striking vehicle; and second, where a PARTS vehicle was the struck vehicle. The latter case serves to inform about any influence those crashes may have on estimated effectiveness when used as a control crash in QIE.

Below are some properties of the provided VMT exposure that influenced analysis and should be considered when interpreting results:

1. 91% of vehicles with VMT estimates (from states with available crash data) did not have an associated crash of any kind (and a higher percentage did not have an associated system-relevant crash).
2. VMT was not available by the state in which the miles were driven, so proxy rules were developed to estimate VMT by state.
3. Many factors (e.g., driver age, driver sex, wet roads versus dry roads) that have previously been shown to influence crash rates could not be associated with VMT.
4. The estimated VMT by calendar year provides good accuracy in aggregate but shows a wide range of accuracy levels for individual vehicles, as shown in Figure 5.
5. Quality assurance rules filtered out vehicles and/or VMT estimates for specific calendar years. The impact of these filters was unequal across OEMs and model years.

Crash data were linked to equipage and VMT based on masked VINs. The vehicle population with VMT was nationwide, so had to be filtered to enable approximate VMT for the states in which crash data were available. Proxy rules included vehicles sold in those states and, if the sale state was not available, included vehicles with VMT recording in the state.

A Poisson regression was performed, using the Generalized Linear Models (GLM) function from "stats" package in R, to investigate the effect ADAS feature equipage had on system relevant crash rates. The Poisson regression was selected due to the data presenting as a rate of events per interval. The response variable was the number of crashes, and VMT was included as an offset. ADAS feature equipage was included as an explanatory variable. Additionally, covariates of model year, state, whether the vehicle was fleet or not, and calendar year were included to control for their influence on crash rates. Other factors exist that are known to affect crash rates (e.g., driver age, driver sex, wet roads versus dry roads) but were not associated with miles traveled and thus could not be included. A dispersion parameter was fit in the Poisson regression through the quasi-Poisson error distribution.

The number of crashes and VMT were aggregated for equipped and unequipped vehicles for each possible combination of levels of the set of covariates and entered into the Poisson regression. However, a Poisson regression including individual vehicles was also run, and notable observations about differences between the aggregated and individual vehicle runs are discussed below.

The Poisson regression using either aggregated data or individual data will always produce equal center estimates for effectiveness of equipped versus unequipped. The standard error and confidence intervals would also match if the data strictly followed a Poisson distribution. However, when fitting a dispersion parameter, the standard errors and confidence intervals can differ between aggregated and individual vehicle Poisson regressions. The individual vehicle Poisson regression had a larger dispersion parameter estimate and associated standard error, which resulted in a wider confidence interval. This is likely due to variance introduced by the following issues:

1. The number of zeros (i.e., vehicles with no crashes in particular calendar years) present in the data did not match well to the assumption of a Poisson distribution.
2. Inaccuracy of VMT estimates for individual vehicles likely produced heterogeneity in rates.
3. The assumption that vehicles were independent across calendar years was likely inaccurate due to similar drivers, driver characteristics, and environmental conditions unaccounted for in the model.
4. Missing covariates likely produced heterogeneity in rates.

A Zero-Inflated Poisson (ZIP) model was considered as a potential solution to modeling overdispersion caused by excess zeros. However, this approach was ultimately not pursued due to the lack of understanding of the mechanisms that would separate always zero observations from the Poisson generated observations, which would have made interpretation of the model results challenging and potentially unreliable. Given these considerations, the decision was made to focus on the Poisson regression with a dispersion parameter, applied to aggregated data, as this approach offered a pragmatic balance between model simplicity and the ability to account for overdispersion in the crash counts. This decision reflects a trade-off between addressing known limitations and maintaining interpretability and feasibility within the constraints of the available data and modeling framework.

One of the purposes of using VMT as an exposure metric was to validate QIE results. There would not be statistical evidence of disagreement (i.e., would not reject null hypothesis of equality) if the confidence interval of the VMT Poisson regression covers the QIE estimate. If the narrower confidence interval produced by the Poisson regression on the aggregated data covers the QIE estimate, then the wider confidence interval (around the same center estimate) produced by the Poisson regression on the individual vehicle data would also cover the QIE estimate.

To compare VMT Poisson regression results with QIE results, QIE was carried out via a logistic regression for AEB on front-to-rear striking and active lateral systems on SVRD crashes using front-to-rear struck crashes as a control. Although the PARTS crash data has information on many more covariates and QIE would allow their inclusion, we chose to match the covariates in the QIE logistic regression to those that could be included in the VMT Poisson regression.

5 Results

The estimated effectiveness of AEB on front-to-rear striking crashes is presented in Table 1. We see good agreement between VMT and QIE. These results also agree with previously reported estimates of ADAS effectiveness by PARTS even though those studies included different model years, vehicle models and segments, and differing covariates in the statistical models.

Table 1. Estimated AEB Effectiveness

Exposure	Estimated Crash Reduction	95% CI	# Front to Rear Striking Crashes	VMT (million)
VMT	50%	(47%, 53%)	Equipped: 6,104 Unequipped: 5,213	Equipped: 66,761 Unequipped: 23,680
QIE	48%	(44%, 51%)	Equipped: 6,104 Unequipped: 5,213	

Table 2 presents the estimated effectiveness of Active Lateral Systems' on SVRD crashes. Like AEB, we see good agreement between VMT and QIE estimates of effectiveness. In both cases the confidence intervals are quite wide due to a limited sample of crashes, in particular unequipped vehicles. The VMT confidence interval for Active Lateral Systems fully includes the QIE confidence interval, which would suggest minimal evidence of a difference. Unlike the QIE confidence interval, the VMT confidence interval covers zero, which would lead to different conclusions about rejecting a null hypothesis of no effectiveness between VMT and QIE.

Table 2. Estimated Lateral System Effectiveness

Exposure	Estimated Crash Reduction	95% CI	# SVRD Crashes	VMT (million)
VMT	13%	(-25%, 40%)	Equipped: 2,352 Unequipped: 773	Equipped: 60,683 Unequipped: 14,789
QIE	15%	(3%, 26%)	Equipped: 2,352 Unequipped: 773	

Finally, Table 3 presents the estimated effect AEB has on Front-to-Rear struck crashes. This was not done to see if AEB is effectively reducing the crashes, but rather to understand the effect front-to-rear struck crashes may have when used as control crashes in QIE. We expect AEB effectiveness to be close to zero for these crashes or at least have a confidence interval overlapping with zero. The confidence interval lies slightly above zero, showing a reduction in front-to-rear struck crashes for vehicles equipped with AEB. This indicates that QIE based models using front to rear struck rates as a control may underestimate[2] the effectiveness of ADAS equipped vehicles in reducing system relevant crashes.

Note that a larger confidence interval was produced (-3%, 14%) by the individual vehicle Poisson regression, overlapping with zero.

Table 3. Estimated Effect of AEB on Control

Exposure	Estimated QIE Control Crash Effect	95% CI	# Front to Rear Struck Crashes	VMT (million)
VMT	6%	(1% , 10%)	Equipped: 25,925 Unequipped: 10,502	Equipped: 66,761 Unequipped: 23,680

[2] QIE looks at ratio of system relevant to control crashes. If the ratio of system relevant to control crashes is lower for equipped than unequipped that would indicate effectiveness. QIE assumes control crashes are system neutral. Using the conceptual framework of equal exposure between equipped and unequipped would imply equal number of control crashes (i.e., ratios of X/C for equipped compared to Y/C for unequipped). If AEB caused a reduction in control crashes, then for equal exposure that would result in less control crashes for equipped vehicles than unequipped. The ratio of system relevant to control would be artificially higher for equipped vehicles (i.e., equipped would be X/[C*[1-Reduction]] versus the assumed X/C) but would be unchanged for unequipped (Y/C), which would result in underestimation of effectiveness.

6 Discussion

The integration of pooled VMT data in this study resulted in a dataset whose size surpassed those typically found in the literature. This dataset enabled a proof-of-concept study on ADAS effectiveness leveraging vehicle-level mileage data to control for exposure.

Despite variability in reporting practices among manufacturers and significant changes over time, the pooled VMT data yielded results that are reasonably consistent with other studies. This consistency underscores the feasibility of conducting safety analyses based on pooled dealer visit and telematics data from multiple manufacturers, even in the face of reporting challenges. It suggests that, with careful management, pooled data can provide a reliable foundation for traffic safety research.

The findings from this study have important implications for best practices in manufacturer reporting. Establishing standardized reporting protocols could enhance the reliability and utility of pooled datasets. Cumulative measures over time, in particular, offer significant benefits. They are robust against issues such as dropped messages and eliminate the need to post-process totals across vast numbers of records, simplifying data management and analysis.

The current analysis indicates while data readings closer to the date of interest improve accuracy, estimates remain useful even with time gaps of several months. While we allowed up to two years between mileage readings and the estimated date, analysis found a higher frequency in readings is beneficial for detecting and excluding poor-quality data. This suggests periodic aggregates, such as annual mileage per VIN, may be adequate for certain types of safety analysis. Even if extended to monthly updates, the data volume would be significantly less than sensitive trip-level data, making this approach both efficient and effective.

The analysis of VMT-based crash rates in this study validates the QIE, with both producing similar results when the data inputs and covariates are matched. Additionally, the VMT-based exposure analysis results are similar to results previously produced by PARTS, with differing data inputs and covariates, reinforcing the reliability of these estimates.

A novel aspect of this research is the use of year-end mileage as an exposure measure. The combination of a large VIN-specific VMT dataset, ADAS equipage information, and police crash reports appears to be unique in the literature. This approach complements QIE by enabling an examination of rear-end struck vehicle rates with and without AEB. Such an analysis is not possible with QIE alone, as rear-end struck rates are typically used as an exposure metric. The results suggest AEB equipage is associated with reduced or neutral rear-end struck rates, thus supporting the efficacy of using rear-end struck rates with QIE to assess road safety. AEB being associated with a reduction in front-to-rear struck rates was also reported by [9] studying pickups using registered vehicle years as the exposure metric.

In conclusion, this study demonstrates the value of pooled VMT data and telematics in advancing traffic safety research. The lessons learned here can inform future efforts to harness these data sources for more effective safety analyses and interventions.

Study Limitations

While this study provided valuable insights into the safety effects of certain ADAS, several limitations must be acknowledged to contextualize the findings and guide future research.

First, the dataset is constrained by a limited set of vehicle models. This restriction may affect the generalizability of the results, as the findings may not fully represent the broader spectrum of vehicles on the road. The focus on specific models could introduce biases related to the unique characteristics of vehicle drivers or the ADAS technologies or executions of those vehicles, potentially skewing the analysis.

Additionally, the study is geographically limited to a subset of states. This geographic concentration may not capture the full diversity of vehicle population proportions, driving environments and conditions across the country, limiting the applicability of the results to regions with different traffic patterns, regulatory environments, or infrastructure characteristics.

A significant limitation is the absence of demographic data. Without this information, it is challenging to account for potential factors that could influence driving behavior and crash risk, such as age, sex, or socioeconomic status. This gap restricts the ability to conduct a comprehensive analysis of how these factors might interact with ADAS features.

Moreover, the dataset lacks information about the driving domain, including road characteristics, weather conditions, and time of day. These contextual factors are crucial for understanding the circumstances under which crashes occur and how ADAS might mitigate risks. The absence of such data limits the depth of the analysis and the ability to draw conclusions about the effectiveness of ADAS in varying driving conditions.

The study also faces challenges related to incomplete reporting from vehicles, with high variability in reporting practices across manufacturers and a lack of accessible data related to the availability or activation of the ADAS at the time of a crash. This inconsistency can lead to gaps in the data, affecting the reliability and completeness of the analysis. Furthermore, there have been large changes in reporting over time, with more comprehensive data available from recent vehicle models. This temporal variability may introduce biases, as newer models with more advanced reporting capabilities could disproportionately influence the results.

Finally, VMT reporting from both telematics and dealer visit sources tends to decline as vehicles age. This drop-off in data availability for older vehicles can limit the ability to assess long-term trends and the sustained impact of ADAS over the vehicle lifecycle. It also poses challenges for evaluating the effectiveness of ADAS in older vehicle populations, which may differ from newer models in terms of technology integration and performance.

In summary, while this study offers important contributions to the understanding of ADAS and traffic safety, these limitations highlight areas for improvement in future research.

7 Conclusion and Future Work

The current VMT study has demonstrated the value of vehicle mileage and vehicle-based data to safety research, establishing a foundation for further exploration. Current findings validate the application of QIE methods for measuring AEB front-to-rear striking crash rates and provide complementary measures of AEB front-to-rear struck crash rates. Additionally, this study provides valuable insights into efficient and effective collection and reporting practices of VMT to support vehicle safety research.

The integration of telematics data represents a pivotal step in refining analytical methodologies and enabling the acquisition of vehicle-level data for more rapid and precise assessments of ADAS and other safety technologies. A key refinement would be to measure vehicle miles driven with ADAS features both available and actively engaged. This refinement is essential for accurately evaluating the effectiveness of systems such as lane keeping assistance, which are frequently deactivated by drivers or rendered unavailable due to environmental or operational conditions [10] [11]. Understanding the prevalence and context of such deactivations is crucial for evaluating the real-world performance of these systems.

As a data-sharing public-private partnership, PARTS is uniquely suited to enable novel research in this space. Additional avenues for future research include enhancing our understanding of relationships between the number and type of miles driven (e.g., when and where miles are accumulated), vehicle safety systems used, driving behaviors (e.g., following distance, speed, and aggressiveness of driving), and crash occurrence. Expanding telematics-enabled exposure metrics will enable the development of novel analytical approaches and foster a more granular understanding of traffic safety. Ultimately, these advancements have the potential to inform more effective infrastructure design and technology enhancements, driving progress in vehicle safety and traffic management.

Acronyms

Term	Definition
ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance Systems
ADS	Automated Driving System
AEB	Automatic Emergency Braking
CSC	Consolidated State Crash
EDT	Electronic Data Transfer
FCW	Forward Collision Warning
GLM	Generalized Linear Model
IQR	Inter-Quartile Range
ITP	Independent Third Party
LCA	Lane Centering Assistance
LDW	Lane Departure Warning
LKA	Lane Keeping Assistance
MITRE	The MITRE Corporation
NHTSA	National Highway Traffic Safety Administration
ODD	Operational Design Domain
OEM	Original Equipment Manufacturer
PARTS	Partnership for Analytics Research in Traffic Safety
QIE	Quasi-Induced Exposure
SUV	Sport Utility Vehicle
SVRD	Single Vehicle Road Departure
UMTRI	University of Michigan Transportation Research Institute
USDOT	United States Department of Transportation
VIN	Vehicle Identification Number
VMT	Vehicle Miles Traveled
ZIP	Zero-Inflated Poisson

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