AI AT THE WHEEL:
THE EFFECTIVENESS OF ADVANCED DRIVER-ASSISTANCE SYSTEMS AND ITS IMPLICATIONS FOR POLICY

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Abstract. Has automakers' use of artificial intelligence in advanced driver-assistance system (ADAS) technologies improved automobile safety? If so, should the government mandate their adoption in all new vehicles? We address those questions with a first of its kind trim-level dataset of the universe of registered automobiles and accidents in Texas over a 9 year period. We find that ADAS technologies reduce the risk of a motorist getting in any type of accident by 10 to 13 percent and reduce the risk of a motorist getting in a single vehicle fatal accident by roughly one third. Despite those benefits, we caution against the government mandating adoption of ADAS in new cars because the external benefits are small, drivers are adequately informed about the benefits of ADAS, and drivers have equitable access to the technologies.

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1. Introduction

Since Ford Motor Company mass produced the Model T more than a century ago, the US automobile industry has gradually introduced notable vehicle safety improvements including headlights, automatic windshield wipers, shatterproof glass, improved braking, advances in body structure, collapsible steering columns, and occupant safety devices. Government policies also have sought to improve automobile safety by requiring motorists to have a valid driver's license, prohibiting driving under the influence of alcohol or drugs, setting and enforcing speed limits, and requiring vehicles to satisfy National Highway Traffic Safety Administration (NHTSA) safety standards.[2]

Beginning in the late 2000s, automakers took an important step forward to improve safety by steadily equipping their vehicles with advanced driver-assistance systems (ADAS) based on artificial intelligence. ADAS consists of a suite of safety features that assist in both the forward dimension (automatic emergency braking and adaptive cruise control), and the lateral dimension (lane departure warning and blind spot collision prevention).[3] ADAS is standard for some vehicle makes, models, and trims, can be purchased as an option for other makes, models, and trims, and is unavailable for purchase at this time for the remaining makes, models, and trims.[4] According to the American Automobile Association, at least one ADAS feature was available in 92.7% of new vehicle models in the United States in 2018.[5]

ADAS distinguishes itself from other automobile safety features because it assists the driver by making its own decisions in response to safety threats in real highway travel settings; for example, it may brake automatically to avoid a collision. Other safety features, such as airbags, enhance safety by reducing the severity of an injury if an accident occurs, but ADAS enhances safety by substituting for a driver's attention to prevent an accident from occurring.

The recent adoption of ADAS in the US motivates our interest in assessing its effectiveness at reducing accident risk. As appropriate for assessing the performance of a new technology, we account for the people who select the technology as well as for how they use it in practice because those choices can reinforce or compromise the intended effects of the technology. In contrast, an

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[2] Government highway expenditures also have been used to improve the safety of the road system.
[3] Except for adaptive cruise control, ADAS features engage autonomously because they are often enabled by default.
[4] In addition to safety technology, a vehicle's trim includes powertrain options, aesthetic features, and comfort amenities
[5] https://www.electronicdesign.com/markets/automotive/article/21126132/how-technology-is-driving-the-democratization-of-adas

engineering analysis, which is the basis for current estimates of the effectiveness of ADAS, does not account for the potential bias of motorists who self-select into vehicles equipped with ADAS nor motorists' potential behavioral responses of driving more aggressively in ADAS equipped vehicles.

To date, ADAS has been voluntarily installed in certain vehicles by automakers and selected by motorists through their choice of vehicle and trim. But recently, the federal government issued one of the most significant changes to car safety standards in years by requiring that all new passenger cars and light trucks be equipped with automatic emergency braking (AEB) systems, an important component of ADAS. Automakers have until the fall of 2029 to ensure that the AEB systems on their 2030 vehicles comply with federal safety standards.[6]

A long line of research, however, has questioned both the justification for and effectiveness of government intervention in motorists' adoption of automobile safety features because consumers' voluntary adoption of vehicles with new safety devices may be producing significant safety improvements without the costs of government intervention. Those costs include some motorists being required to pay higher vehicle purchase prices that exceed their valuations of the benefits of the safety devices and some motorists offsetting the benefits of government mandating the adoption of automobile safety features by driving more aggressively.[7]

Thus, our assessment is further motivated by policymakers' apparent dissatisfaction with the progress of motorists' adoption of ADAS in their vehicle choices as shown by their mandating the adoption of AEB systems in all new 2030 vehicles. We discuss the various cost-benefit and

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[6] Under the rule, all new vehicles would be required to have a version of automatic emergency braking that is "much more effective at much higher speeds." Specifically, all cars would need to be able to stop and avoid contact with a vehicle in front of them when traveling up to 62mph; vehicles traveling as fast as 45mph would need to come to a complete stop to avoid hitting pedestrians; and braking systems would be required to detect pedestrians and cyclists at night. https://www.nhtsa.gov/sites/nhtsa.gov/files/2024-04/final-rule-automatic-emergency-braking-systems-light-vehicles_web-version.pdf Currently, no commercially available automatic emergency braking technologies satisfy these stringent technical requirements.

[7] As an example of motorists choosing to avoid the cost of government intervention in automobile safety, Thaler and Rosen (1976) and Mannering and Winston (1987) found that although federal law in 1968 required seat belts to be installed in all vehicles except buses, many motorists did not wear them based on a rational cost-benefit assessment of the time and bother costs to fasten seat belts and their effect on reducing the probability of a fatal accident. As an example of offsetting behavior, Peltzman (1975) argued that even when seat belts were fastened, motorists reduced their technological effectiveness by speeding, thereby maintaining their exposure to accident risk. Winston, Maheshri, and Mannering (2006) found that motorists' increase in risky driving behavior appeared to offset the technological effectiveness of airbags.

equity considerations that should guide the government's decision whether to mandate AEB systems and provide suggestive evidence on their magnitudes.

As noted, the availability of ADAS varies at the model year-make-model-trim level. Thus, to execute our analysis, we aggregate data on accidents and driving to this level, which allows us to assess the effectiveness of ADAS by comparing the safety performance of extremely similar *vehicles* with and without ADAS. To the best of our knowledge, our paper is the first to use modern data collection methods to extract the detailed data that is necessary to conduct a trim-level analysis of automobile safety.

Generally, our approach stands in contrast to the vast empirical safety literature that conducts analyses at the incident level in an attempt to identify the determinants of automobile accidents (for example, Haghani and Bliemer (2023) and Anderson and Auffhammer (2014)). By doing so, that literature is subject to selectivity bias because precisely who chooses to drive what vehicles at what specific times of day under which specific driver and driving conditions is unlikely to be random. Circumventing this bias requires, at a minimum, researchers to identify only treatment effects on accident severity conditional upon an accident occurring. However, a conditional analysis cannot account for accidents that have been prevented.[8] In contrast, our approach enables us to identify the unconditional effectiveness of ADAS availability with an identification strategy that can address the various selection issues that arise. To implement this approach, we require information on the universe of vehicles on the road in a given geographical area, including those vehicles that have not been involved in accidents.

We fulfill this information requirement by constructing a panel dataset comprised of all registered vehicles in Texas from 2010 to 2018. We link the dataset to a record of all accidents for which a police report was filed in Texas during this period, enabling us to construct the accident history of the universe of registered vehicles.[9] Although we include the universe of vehicles registered in Texas, some of which get into accidents (and most of which do not), we exclude

[8] Some analyses of auto safety (for example, Edlin and Karaca-Mandic (2006)) aggregate data by driver type to estimate the determinants of drivers who are involved in fatal and non-fatal accidents. However, because we are concerned with the effectiveness of a vehicle attribute, we aggregate our data by vehicle type.

[9] Texas takes all automobile accidents seriously. Even in a minor accident with no injuries, drivers who leave the scene of the accident without calling the police could be charged subsequently with a misdemeanor. State law mandates that drivers involved in an accident causing injury, death, or property damage exceeding $1,000 must report the incident to law enforcement.

vehicles not registered in Texas in our initial analysis because we do not observe out of state vehicles that are not involved in accidents.[10]

Finally, we combine the vehicle accident histories with a panel dataset that we construct that identifies the availability of ADAS-related safety features on each trim of every vehicle that was registered during the sample period. The two data sources are merged via a specialized matching procedure using machine learning techniques that decodes the precise trim level of a vehicle from its Vehicle Identification Number (VIN). In sum, our data set consists of the universe of vehicles in Texas, including vehicles that have and have not been involved in accidents and vehicles that are equipped and not equipped with ADAS-related safety features. Our findings should be reasonably representative of the US as a whole because Texas is a large state with a diverse population and fleet of vehicles, which is driven in urban and rural environments that vary in geography, weather, and density.

Given this data set, we can meet the fundamental challenge of identifying the causal effect of a new technology on automobile safety—the adoption of the technology is generally non-random—by exploiting the plausibly exogenous variation in the availability of ADAS on different vehicles over time. As the new technology (treatment) varies by vehicle, we compare the aggregate safety performance of vehicles with and without ADAS, as opposed to comparing the disaggregate safety performance of individual drivers. Using the latter approach, the effect of ADAS would be identified only under the questionable assumption that a driver's propensity to purchase an ADAS-equipped vehicle was uncorrelated to their attitudes toward safety and their driving abilities (perhaps conditional on some small set of observable driver characteristics).

In our approach, we leverage the fact that ADAS became available at different times for different trim levels—notably within vehicles of the same make and model.[11] We therefore identify the causal effect of ADAS on accidents under the weaker assumption that drivers did not systematically opt for higher trim level vehicles solely because of the availability of ADAS. Of course, drivers of higher trim vehicles are likely to differ from drivers of lower trim vehicles in some respects. However, vehicles of different trim levels vary in multiple dimensions by offering

[10] As part of our sensitivity analyses, we explore later how our results would be affected if we included both in-state and out of state vehicles in the accident data. As expected, our main findings are not affected because out of state vehicles account for a very small share of accidents in Texas.
[11] Wåhlberg and Dorn (2023) assess the effectiveness of vehicle electronic stability control (ESC) on fatal crash rates, but they do not compare cars' safety performance with and without ESC.

dozens of appealing features, many of which are related to comfort and aesthetics and not to safety. This fact lends credence to our identifying assumption, which relies on a combination of the choice of higher trim versus lower trim *and* the timing of ADAS availability.

We also recognize that the effects of self-selection in influencing the effectiveness of ADAS may be reflected in drivers' risk preferences that are manifested in several ways. That is, those preferences may affect when drivers decide to adopt a vehicle with ADAS; whether and how they drive in different highway conditions; and whether and how they drive in different types of vehicles.

Fortunately, data are available that enable us to test directly for systematic patterns related to drivers' risk preferences that suggest whether they self-select into vehicles equipped with ADAS technologies. We assembled a large sample of Texas households who owned vehicles and we obtained from Acxiom, a database marketing company, many of those households' socioeconomic characteristics. We also collected data on the households' vehicle safety records. Using these data, we provide evidence that the type of motorists who purchase vehicles with higher trim is not systematically affected by the availability of ADAS in higher trim vehicles. We also provide evidence that the evolution of the crash rate of drivers who never purchased ADAS equipped vehicles is similar to the evolution of the crash rate of drivers who eventually purchase ADAS equipped vehicles. Finally, we explore empirically the heterogeneous effects of ADAS across a wide range of vehicle characteristics, such as price and size, and highway travel conditions, such as clear weather, which are known to be positively correlated with the purchase and driving behavior of safer drivers. We provide evidence that the heterogenous effects of ADAS on accident outcomes do not vary systematically across vehicle and travel characteristics.

Importantly, we find that ADAS is highly effective at improving automobile safety even after accounting for drivers' behavioral responses to its availability and installation. Specifically, ADAS technologies reduce the risk of a motorist getting in any type of accident by 10 to 13 percent and reduce the risk of a motorist getting in a single vehicle fatal accident by roughly one third. ADAS has a small and statistically imprecise effect on reducing the risk of a motorist getting in a multivehicle fatal accident, but we suggest that ADAS is likely to reduce the fatality risk of those types of accidents as a greater share of the nation's vehicle fleet is equipped with autonomous vehicle safety features. Bear in mind that other safety features, such as airbags and seatbelts, do not reduce the probability that a driver will get in an accident. In this respect, ADAS represents a significant advance in automobile safety by substituting effectively for a driver's attention and by providing suggestive evidence that fully autonomous vehicles will dramatically improve highway transportation safety.

Notwithstanding these economically significant benefits, we provide four reasons that collectively indicate that it is currently inadvisable for policymakers to mandate the installation of ADAS technologies in new vehicles. First, motorists are reasonably well-informed about the benefits of ADAS because, on average, the motorists who purchase vehicles with ADAS appear to be willing to pay for their significant installation costs. Second, access to ADAS is equitable and does not appear to be affected by supply-side distortions. Third, the mandate would force a sizeable share of motorists to incur considerable costs, on net, if their valuation of the improvements in safety attributable to ADAS were exceeded by ADAS installation costs. Of course, this point could be weakened in the future if the cost of installing ADAS falls significantly or if consumers' perceived benefits of ADAS significantly increases. Finally, we conclude that the external benefits of ADAS, which amount to eliminating the social costs of multi-vehicle accidents that are prevented, are likely to be small.

2. Estimating the Efficacy of ADAS

The staggered rollout of the availability of ADAS over time and across different automobile makes, models and trims generates temporal and cross-sectional variation in registered vehicles' safety features that enables us to identify the causal effect of ADAS on accident risk. We construct aggregate versions of the key variables, ADAS availability and accidents, to execute the empirical analysis, and then explain our specification to estimate the effect of ADAS availability on accident risk.

ADAS Availability

In most safety analyses, a vehicle type, which we index by i, is defined as a combination of make and model. However, within a make-model combination in our analysis, some vehicles (e.g., luxury editions) may have ADAS and others (e.g., standard editions) may not. We therefore expand the definition of vehicle type as a combination of make, model and trim, where trim levels, defined in the data section, are indexed separately by j.

Crucial to our analysis is that the availability of ADAS for a given vehicle make and model may vary over time because it is not available in earlier model years of some vehicles, but it is available in later model years. Moreover, some vehicle makes and models may never have ADAS available during the sample period. Let y index the model year of a given vehicle type. Then, our treatment variable, the availability of ADAS, which we denote by the dummy variable S_{yij}, varies at the model year y, make-model i, and trim level j.

Accidents

For each vehicle in each calendar year of our sample, we observe the vehicle's model year, type (make-model), trim level, whether it was involved in an accident, and if so, the accident severity (ranging from property damage only to a fatal accident). We denote by t the calendar year, which will generally differ from the model year, of a specific year in a vehicle's accident history. Because we are interested in the effect of a treatment that occurs at the vehicle level, we aggregate accident outcomes to the model year-type-trim-calendar year level and denote by A_{yijt} the total number of accidents of a given severity that vehicles yij had in year t.

The temporal and cross-section variation in our panel is distinctive because it contains two different temporal dimensions: a vehicle's model year y and calendar year t. Although the accident outcome varies over the calendar year dimension, the treatment varies only over the model year dimension y—older models of a vehicle type that were untreated remain untreated even if newer models of that type are treated. Hence, a different treatment variable may be observed at a given $t \geq y$. We exploit the variation in the treatment variable within vehicle type and across trim, model years and calendar years to identify the causal effect of ADAS on accidents.

In table 1, we illustrate the organization of our data for a single vehicle type, the Acura MDX, using the calendar year as the primary temporal dimension for the 2000 to 2019 sample period.[12] The Acura has three trim levels that we denote as Low (L), Medium (M), and High (H), each associated with the period, if any, that they were equipped with ADAS.[13] Vehicles with a low trim level were never equipped with ADAS during our sample period; vehicles with a medium

[12] Note the model year for vehicles manufactured up to June 2018 will be 2018, but the model year for any of the vehicles in our sample manufactured from July through December in each year (for example, 2015) can be advertised as the next model year. Hence even though our sample period corresponds to 2010-2018, it includes some model year 2019 vehicles.

[13] Manufacturers distinguish trims by a large number of features and frequently change the names of different trims for marketing purposes. For example, the 2018 Acura MDX was offered in 5 trim configurations that were marketed in three trim levels: Standard, Technology and Advance. Meanwhile, the 2015 Acura MDX was marketed in 4 trim levels: Base, Advance/Entertainment, Tech, and Tech/Entertainment. Because we are analyzing the effects of ADAS on safety and we wish to maintain a consistent treatment of makes and models over time, we aggregated all vehicles of a given make and model that introduced ADAS in the same model year as a single trim (in this case, Low, Medium or High).

trim level were equipped with ADAS in model year 2018 but not before that calendar year; and vehicles with a high trim level were equipped with ADAS in 2015 but not before that calendar year. The three different trim levels of Acura MDX's on the road during our sample period enable us to define the treated vehicles as Acura MDX's with high and/or medium trim levels that include ADAS. Our untreated or control vehicles are Acura MDX's that do not include ADAS. We define all of the other treated vehicle types and control vehicles in our sample in the same way.

Specification

Previous safety research (e.g., Maheshri and Winston (2024)) has specified vehicle accidents A_{yijt} in a Poisson regression framework because accidents take on small, discrete, non-negative values (Cameron and Trivedi (1998)). Although some empirical analyses in the transportation literature estimate accident equations using a negative binomial model, this is inadvisable because, as pointed out by Wooldridge (1999), the negative binomial estimator is a non-robust estimator of conditional mean parameters, and this weakness is exacerbated when using fixed effects.[14] Negative binomial regressions may be appropriate if the objective is simply to maximize the fit of the model and there is overdispersion in the dependent variable. However, for causal inference where we are interested in a mean causal effect, the Poisson QMLE estimator discussed by Gourierieux et. al. (1984) yields consistent estimates of the effect of interest without the distractions of variance assumptions.

We therefore specify our models of accidents and fatal accidents as:

$$A_{yijt} = exp\big(\beta\, S_{yijt} + \lambda_{ijt} + \lambda_{iyt} + \epsilon_{yijt}\big)\ , \qquad (1)$$

where S_{yijt} is a dummy variable equal to one if ADAS was available either as standard equipment or purchased through an optional package on vehicle yij in year t and zero otherwise; λ_{ijt} are make-model-trim-calendar year fixed effects; λ_{iyt} are make-model-model year-calendar year fixed effects; and ϵ_{yijt} is an error term.[15]

[14] As Gourierieux et. al. (1984) show, the negative binomial estimator requires both mean and variance to be correctly specified, whereas the Poisson estimator only requires the mean to be correctly specified. Moreover, as Wooldridge (1999) has noted, the negative binomial estimator only "pretends" to solve the problem of over- or under-dispersion of data, but this is only true if the variance is correctly specified; otherwise, misspecification bias will be inherited. Perhaps most critically for our application, negative binomial estimators suffer from the incidental parameters problem and also are scale dependent.

[15] Data on specific vehicles that were purchased with ADAS as an optional package are not available. However, when a vehicle, defined by make and model, offers ADAS features as an option instead of as standard, most consumers who select that vehicle also are likely to purchase the optional ADAS features. The reason is that the entire trim package of a vehicle that offers optional ADAS features is usually more expensive than the entire trim package of the same or

The key identifying assumption that enables parameter β to be interpreted as the causal effect of the availability of ADAS on selected vehicles on the total number of accidents is that $cov(S_{yijt}, \epsilon_{yijt} | \lambda_{ijt}, \lambda_{iyt}) = 0$. That is, motorists who purchase higher trim vehicles during the first model year that ADAS is made available in those vehicles are not systematically different from the motorists who purchase higher trim vehicles of other model years. We provide several pieces of empirical evidence to support this assumption. Based on early experiences with autonomous vehicles in controlled testing environments (Blanco, et. al. (2016), Mosquet, Andersen, and Arora (2016)), we expect the availability of ADAS to reduce accidents. But as discussed in Maheshri and Winston (2025), the quantitative findings in controlled testing environments should be viewed with caution because they are likely to be inflated by using a non-random sample of drivers.

3. Data

We constructed a data set consisting of all the registered vehicles in Texas from 2010 to 2018 along with their trim, which we used to identify whether a given vehicle is equipped with ADAS. We used leading vehicle data aggregators that describe the available safety features in all new vehicle trims, including ADAS, to identify the vehicles equipped with ADAS during the sample period.[16] Then, for each vehicle we merged information from the universe of Texas police accident reports to construct its detailed accident history. To the best of our knowledge, this is the first data set at the vehicle trim level that has been used to assess the efficacy of vehicle safety features.

Extracting safety features from Vehicle Identification Numbers (VINs) and then aggregating vehicles to the trim level is a formidable task. It requires matching unstructured descriptive data from auto manufacturers to vehicle trims that are only partially identified by their VIN and then classifying vehicles into meaningful groupings of trims in a consistent manner. We decoded the VIN of every vehicle in our sample using a commercially available VIN decoder. The decoder identified each vehicle down to the trim level, which is critical for our analysis because

similar vehicle that does not offer ADAS as an option. Thus, consumers who do not want the optional ADAS features would, in all likelihood, decide to reduce their costs by simply choosing a similar vehicle that does not contain a trim package that gives them the opportunity to purchase ADAS as an option. Anecdotal evidence obtained from car dealers was consistent with this characterization of consumer behavior.

[16] Vehicle data aggregators use automotive data aggregation platforms, which are centralized systems designed to collect, organize, and process data generated by vehicles within the automotive ecosystem.

different versions of the same vehicle make and model have different safety features.[17] We then collected detailed information from data aggregators, such as TrueCar and MotorTrend, by scraping their websites and employing string manipulation techniques to verify the availability of ADAS for each vehicle. A more detailed description of how we extracted safety features from Vehicle Identification Numbers (VINs) and aggregated vehicles to the trim level is available in the Appendix A. In all, we constructed a panel of annual and fatal accidents from 2010 to 2018 for 6,268 distinct vehicle types defined as a unique model year-make-model-trim combination.

In Figure 1, we present the evolution of ADAS availability for vehicles in our sample during calendar years 2010-2018. Panel A shows that vehicle trims equipped with ADAS safety technology were relatively scarce for most of our sample period, though they gradually became more common after 2015. Indeed, Panel B shows that while the number of vehicles equipped with ADAS safety technology represents a small (less than 20%) share of all vehicles throughout our time period, newly registered vehicles are increasingly more likely to be equipped with ADAS towards the last few years of our sample period. This pattern reflects the fact that vehicles are infrequently purchased durable goods; hence, there is a considerable delay between the availability of a new safety innovation and its adoption by motorists.

The introduction of ADAS could affect driving intensity, as measured by vehicle miles travelled (VMT), which could confound our findings on the safety effects of ADAS. To explore this possibility, we constructed a subsample from our main sample of vehicles that contained the VMT for each vehicle in the subsample. The information for a vehicle's VMT was obtained from the Texas Commission on Environmental Quality (TCEQ). The 14 largest counties in Texas require each vehicle to be subjected to emissions testing annually prior to being registered. Among other information, TCEQ collects the VINs of the vehicles and the exact annual odometer readings for each registered vehicle in 14 counties, from which we are able to construct average annual measures of VMT for each vehicle type.

Finally, we collected data to explore whether the availability of ADAS safety features led consumers to self-select systematically into ADAS-equipped and non-equipped trims. We obtained data from Acxiom for more than 200,000 randomly selected registered vehicle owners in Texas from our main sample containing information about their race, income, marital status, household

[17] Using the example in table 1, the Acura MDX high level trim is called the Type S Advance, which made ADAS available in model year 2015. The low level is the base trim, which has not made ADAS available.

size, and propensity to adopt new technologies. We use the data to construct the average demographic characteristics of owners of each vehicle type in our sample. We then estimate whether those characteristics when interacted with the availability of ADAS features have distinct effects on accident outcomes, which could be interpreted as suggesting that consumers are self-selecting into ADAS-equipped and non-equipped trims based on observed influences.

In figure 2, we present a flow chart to summarize the sequence of the data collection and construction process, the variables collected, and the key summary statistics for the variables. We use the final data set for our estimations. As noted, Appendix A provides a detailed description of the process of linking the data from the vehicle registrations, police accident reports, and trim level attributes to identify whether ADAS safety technology was available on each vehicle registered in Texas.

4. Results

Table 2 presents the effects of the availability of ADAS on all accidents and on fatal accidents as incidence risk ratios (IRRs) to facilitate interpretation of the estimates. An IRR greater than 1 corresponds to a positive effect on vehicle accidents, and an IRR less than 1 corresponds to a negative effect on vehicle accidents. We did not specify accident and fatality rates per vehicle mile of travel because the adoption of ADAS is likely to simultaneously influence VMT as well as accidents and fatalities. Even if one of those influences were small, it would still prevent us from determining the distinct effects of ADAS on accidents and fatalities. However, we conduct sensitivity tests to assess the effect that the adoption of ADAS has on VMT.

In each regression, we restrict our sample to model year-make-model-trim combinations with at least ten registered vehicles to ensure that the results are not affected by rare vehicles, such as Ferraris.[18] We also restricted the sample to vehicle types that are equipped with ADAS at some point during the sample period to ensure that the results are not affected by variation among never treated vehicles; when we relaxed this assumption and included never treated vehicle types, our findings were unchanged.

[18] If we eliminate the assumption, our standard errors increase but the coefficients obtained with and without the assumption are not statistically indistinguishable

Basic Findings

We show in table 2 that the availability of ADAS reduces the total number of accidents of a given vehicle and trim type by 13% in single vehicle accidents (column 1) and by 10% in multivehicle accidents (column 2), and the effects are statistically significant. Bear in mind that only a very small share of the entire vehicle fleet is equipped with autonomous vehicle safety features, so ADAS may be slightly less effective in reducing multivehicle compared with reducing single vehicle accidents because the other vehicle involved in a multivehicle accident is unlikely to be equipped with autonomous vehicle safety features. As more of the nation's vehicle fleet is equipped with autonomous vehicle safety features, we speculate that ADAS will be equally effective in reducing single and multivehicle accidents.[19]

ADAS technologies are even more effective at reducing single vehicle fatal accidents as their total number involving a given vehicle and trim type is reduced by roughly one third and the effect is statistically significant (column 3). For example, a lane departure warning could wake up a drowsy driver who is on the road by herself and prevent a fatal accident resulting from the driver running into a retaining wall or driving over an embankment at high speed. Thus, the lane departure warning effectively substitutes for a driver's attention by itself to prevent a fatal single vehicle accident.

However, we find that ADAS technologies have a small and statistically insignificant effect on reducing multivehicle fatal accidents (column 4). As we discussed, the effectiveness of ADAS—or our ability to identify its effectiveness—could be limited in preventing multivehicle fatal accidents because the other vehicle involved is unlikely to be equipped with autonomous vehicle safety features. Thus, we expect as more vehicles are equipped with autonomous vehicle safety features, ADAS will be more effective at reducing fatalities in multivehicle accidents.[20]

As a check that our results are not caused by changes in driving intensity, we present the effects in Table 3 of ADAS availability on vehicle miles travelled. We are unable to obtain

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[19] The introduction of more advanced autonomous driving technologies that allow for communication between vehicles may generate greater safety benefits for multivehicle accidents, but such technologies are not likely to be developed in the near future.

[20] Wooldridge (2023) proposes a method to estimate treatment heterogeneity by using a robust two way fixed effects estimator for a Poisson regression. We used his estimator here as a robustness test of our findings and obtained slightly larger but less precise average treatment effects of ADAS. The loss in statistical precision arises because the estimator proposed by Wooldridge is less efficient than the simpler estimator that we used here. In any case, our quantitative estimates of the effects of ADAS on automobile safety appear to be consistent with those obtained by using the more sophisticated estimator.

statistically significant effects, but based on the estimates in specification (2), we can rule out that the availability of ADAS technology will not *reduce* VMT by more than 4%, which implies that changes in VMT cannot explain the sizeable effects that ADAS availability has on all and fatal accidents.[21]

Heterogeneity

In Figure 3, we show the extent that the effects of ADAS on accidents vary in any systematic way with vehicle characteristics, which could have implications for consumers' selective purchase behavior of vehicles when ADAS is available. Generally, we find little heterogeneity in the effects of ADAS in reducing accidents based on vehicle size, price, and manufacturer nationality, with the exception that its availability appears to be more effective in lighter than heavier vehicles. Because safer drivers tend to purchase larger, heavier, and more expensive vehicles, those findings are consistent with our maintained assumption that safer drivers do not systematically switch into safer vehicles. We find no systematic heterogeneity in the effects of ADAS technologies on fatal accidents.[22]

The effectiveness of ADAS on accidents also may vary by driving behavior and conditions when an accident occurs. These findings also could reflect selectivity to the extent that more risky drivers tend to purchase vehicles with ADAS features because they are more likely than less risky drivers to drive more dangerously and to drive in more dangerous conditions. ADAS could therefore possibly offset risky drivers' choices of how, when, and where to drive. Figure 4 shows, however, that there is no evidence of heterogeneity in the effects of ADAS on all accidents by speed of crash, roadway type, roadway conditions, weather conditions, and day or week or time of day. If anything, ADAS appears to compress drivers' risk profiles by sufficiently offsetting drivers' choices that may increase accident risk. Although we find some heterogeneity for accident conditions in our point estimates for fatal accidents, those differences are not statistically significant.

[21] For sensitivity purposes, we also explored whether any of the preceding findings were affected when we included both in-state and out of state vehicles in the accident data. As we expected, none of our findings were materially affected because based on our data on total accidents in Texas, out of state vehicles account for only about 5% of all the vehicles.

[22] We are unable to estimate precise heterogeneous effects on ADAS on fatalities for many of the vehicle type/weight/MSRP/automaker categories, in all likelihood because of the infrequency of fatal accidents.

5. Potential Sources of Bias That Could Affect the Interpretation of Our Findings

We have assessed important potential sources of bias to our estimates of the effects of ADAS technologies on motorists' safety. We now explore in depth the three primary potential sources of bias to our estimates that could affect the *interpretation* of our finding that ADAS has significant effects on reducing all accidents and fatal accidents: selection bias, offsetting behavior, and contamination of the control group.

Selection Bias

We have stressed that drivers' decisions to self-select into treatment—that is, drive a vehicle with ADAS safety features—is the main source of bias in our analysis because it would indicate that instead of being random, drivers' adoption decisions may be strongly correlated with their safety preferences and behavior. If, for example, safer drivers were systematically more likely to adopt ADAS than were riskier drivers, then our estimates of the effects of ADAS on automobile safety would be biased upwards. Conversely, our estimates of the effects of ADAS on automobile safety would be biased downward if riskier drivers were more likely to adopt ADAS than were safer drivers. The latter behavior would be more relevant in the case of a safety feature like ADAS that can compensate for a driver's riskiness, instead of a safety feature like airbags that does not compensate for a driver's riskiness but engages *after* a vehicle is involved in a collision.

Either of these issues would constitute a failure of the parallel trends assumption underlying our identification strategy. We clarify how this is less of a concern by respecifying our empirical model of accidents given in equation (1) as:

$$A_{yijt} = exp\left(\sum_{\tau=-3,-1,1\ldots4} \beta^{\tau} \times 1\left(\tilde{y}_{ij} - y = \tau - 1\right) + \text{controls} + \lambda_{ijt} + \lambda_{iyt} + \epsilon_{yijt}\right) \qquad (2)$$

where $\tilde{y}_{ij}$ denotes the model year in which vehicle ij is first equipped with ADAS and $1(\cdot)$ represents the indicator function. The coefficients β^{τ} correspond to the effect of ADAS in the τ vehicles equipped with ADAS. Finally, we include $1\left(\tilde{y}_{ij} - y < -3\right)$ and $1\left(\tilde{y}_{ij} - y > 4\right)$ as controls to normalize all effects relative to the model year just prior to treatment (e.g., 2014 for the high trim Acura MDX available in 2015). As before, we estimate the model using the sample of vehicles that were equipped with ADAS at some point during the sample period; we expect the IRR associated with β^{τ} for $\tau < 0$ to be equal to 1 if our estimates did not suffer from self-selection, i.e., there should be no treatment effect in model years prior to treatment.

We present regression results in an event-study style plot in figure 5 showing that the effectiveness of ADAS at reducing accidents and especially at reducing fatalities increases with the model years that ADAS technologies are available on higher trims.[23] There are two potential explanations for this pattern: (1) ADAS reduces the prevalence of accidents by an amount that is quantitatively consistent with the parameter estimates in column 2 of table 2, which are based on our original specification in equation (1), or (2) drivers systematically switch to ADAS equipped trims only when they are made available, and they avoid higher level trims in earlier model years when ADAS was not available.

We reject the second explanation because higher trim vehicles differ from their lower trim counterparts in a variety of important dimensions, not just in the availability of ADAS. Those dimensions include non-ADAS vehicle safety features, such as side curtain and seat mounted side impact airbags, as well as non-safety features, such as a premium leather collection. In Appendix B, we report a complete list of the 15 non-ADAS and non-safety related trim features that were available for vehicles with high trim, but not for vehicles with low trim. The fact that trim choice is influenced by more than just the availability of ADAS lends credence to our first explanation that the pattern of results is credibly aligned with the estimates of the effect of ADAS on all accidents and fatal accidents.

We also provide direct evidence against the claim that the findings are influenced by systematic self-selection of safer drivers into ADAS equipped vehicles by estimating the effect of ADAS availability on the demographic characteristics of adopting households. We accomplish this by replacing the dependent variable in our main specification (equation (1)) with a new dependent variable to obtain:

$$X_{yij} = exp\left(\beta_X\, S_{yij} + \lambda_{ijt} + \lambda_{iyt} + \epsilon_{yij}\right), \qquad (3)$$

where X_{yij} is a demographic characteristic of owners of vehicle yij.[24] Recall that we obtained this variable from a survey by Acxiom, which was conducted for a given calendar year and did not

[23] We refer to the plot as "event-study style" because our data is organized along two time dimensions, calendar year and model year. Accordingly, a given make-model-trim vehicle will contribute different numbers of observations to the estimation of each effect shown in Figure 2. For instance, the 2014 Acura MDX contributes 5 observations to the estimation of the point with -1 model years because ADAS was available in the higher trim calendar years 2014-2018, but the 2016 Acura MDX contributes only 3 observations to the estimation of the point with +1 model years because ADAS was available in higher trim calendar years 2016-2018.

[24] We continue to estimate the specification using Poisson regression because the demographic variables are non-negative with a small number of values. Using Poisson regression in such instances has become common practice.

vary by calendar year. The parameter β_X represents the effect of ADAS availability on an average demographic characteristic of owners. If, for example, drivers differentially sort into ADAS enabled vehicles *because ADAS is newly available*, we would expect to find that our estimate of β_X would be statistically significantly different from zero because the adoption of ADAS was associated with drivers that had certain demographic characteristics.

We present estimates of β_X for a variety of household demographics in figure 6, which again suggests that drivers do not systematically select into ADAS equipped vehicles. Drivers who switch to ADAS equipped trims immediately after the availability of ADAS are slightly more likely to be male, educated, and married, but they are of similar age, from similar sized households, and earn similar incomes. Not surprisingly, these drivers have a higher propensity to own more vehicles and to adopt new technologies. To the extent that there are statistically significant differences between drivers who opt into higher trims when ADAS becomes available, the effects for virtually any characteristic are very small (less than a 5% change).[25] In sum, the evidence bolsters our claim that the findings of ADAS's efficacy in improving safety cannot be explained by selection.

Finally, Figure 7 provides additional circumstantial evidence against the presence of selection bias by showing that over time the safest drivers did not disproportionately switch to vehicles equipped with ADAS when those safety features were first made available. If this were the case, we would expect the earliest adopters of ADAS equipped vehicles to have fewer accidents (pre-adoption) than later adopters of ADAS vehicles (pre-adoption). However, the pre-adoption trends of the crash rates for all groups of drivers are roughly parallel and at similar levels. As we would expect, given the effectiveness of ADAS, the crash rate of drivers who never switched into ADAS equipped vehicles is somewhat higher than the crash rate of drivers who switched into ADAS equipped vehicles at some point during our sample period.

<u>Offsetting Behavior</u>

A second potential source of bias to our estimates is that the adoption of ADAS might affect a driver's *behavior* on the road. For example, a driver with ADAS might take more risks while driving, like texting and paying less attention to traffic conditions, which would offset the safety

[25] The only exception is that Black drivers adopt ADAS equipped trims when they are first made available at close to a 20% change. But the fact that their response is not accompanied by any other demographic shift among all drivers strongly suggests that it is not correlated with the safety preferences of Black drivers only.

benefits of ADAS. Alternatively, because ADAS features include auditory and visual warnings to drivers when other vehicles are approaching, ADAS may induce drivers to make a safety augmenting response. In any case, given that our interest is to estimate the effect of ADAS on automobile safety in *actual* driving conditions instead of the controlled environments typically studied by engineers, it is appropriate for any change in drivers' behavior in response to the adoption of ADAS to be incorporated in our estimates. Our estimates of the heterogeneous effects of ADAS by vehicle characteristics, however, did not suggest that drivers' risk preferences led them to systematically change their behavior in response to adopting ADAS.

Contamination and Externalities

A final potential source of bias could be caused by *contamination* of the control group, which could occur because treated and untreated vehicles may periodically be involved in accidents with each other. Thus, any safety improvement in the treated vehicles, for example, due to the adoption of ADAS, also may improve the safety of untreated vehicles and cause an estimate of the effectiveness of ADAS safety features—or any other safety features—to be biased downward because it does not account for the positive spillover of safety accruing to vehicles that are not equipped with those safety features.

All observational analyses of accident data that are generated when treated and untreated vehicles share the same roadways will be susceptible to contamination bias, but the bias is mitigated in our analysis for two reasons. First, the vast majority of vehicles (new and used) on the road during our sample period did not have ADAS available as an option at the time of manufacture.[26] Second, nearly 50% of the fatal accidents in our sample were single-vehicle accidents.

Moreover, the potential for large externalities from ADAS adoption is significantly reduced because the main contributor to the costs of automobile accidents is fatal accidents, while we find ADAS to be effective only at reducing single vehicle fatal accidents, which has no scope for externalities. In Appendix C, we perform a suggestive quantitative exercise and find that the external benefits of ADAS are likely to be on the order of 10% of the direct benefits. Thus, even if we are underestimating the external benefits by half, we conclude they are of second order

[26] Slightly more than 25% of all the vehicle models in our sample have ADAS, while the share of the total number of vehicles on the road that have ADAS is much smaller.

importance at best and that the case that our estimates are significantly biased downward calls for much stronger evidentiary support

6. Guidance for Mandating ADAS for New Vehicles

As noted, the US federal government has mandated that automakers equip all new model year 2030 passenger cars and light trucks with automatic emergency braking (AEB) systems by 2029. The European Union has already mandated that new and existing vehicles be equipped with AEB systems. Policymakers in the US and in other countries may go further and mandate that all new and possibly existing vehicles be fully equipped with ADAS safety features. We can provide guidance on how to analyze whether such a mandate would be socially beneficial.

There are three primary justifications for government to mandate that new vehicles be equipped with ADAS safety features. First, there is a large potential external benefit to people from ADAS, which reduces the divergence between the private and social costs of driving. Second, motorists tend to undervalue the safety benefits of ADAS and thus do not choose to include those safety features in their choices of vehicle makes, models, and trims. Their uninformed choices may make themselves and other people worse off. Third, access to ADAS safety features is inequitable because of supply-side distortions. Those justifications must be assessed and even if they are found to be valid, they must be balanced against the costs borne by consumers who are forced to pay higher prices for ADAS-equipped vehicles but do not value the safety benefits from ADAS by as much as the price increase.

We have found that ADAS is effective at improving automobile safety. But we argue that the available evidence suggests that it is premature for policymakers to enact a mandate to require ADAS features to be installed in all new vehicles because we cannot conclude unambiguously that any of the preceding conditions to justify a mandate are met. At the same time, it does appear that a mandate would force consumers to incur nontrivial costs. Of course, the available evidence and our caution against mandating ADAS are subject to revision as the public gains more experience with driving ADAS-equipped vehicles and as new evidence that pertains to the desirability of the government mandating the adoption of ADAS in new vehicles is accumulated.

The External Benefits of ADAS

Estimating the full external benefits of an automobile safety feature is a challenging empirical problem because it is difficult to determine whether a safety feature could have prevented other people besides the driver from being injured or killed in an accident. To the best of our knowledge, estimates of such benefits are not available in the literature nor have policymakers offered conjectures about the magnitude of those benefits. For example, NHTSA (2023b) assesses the societal impact of motor vehicle crashes but does not attempt to include any evidence on the external benefits of automobile safety features. Given NHTSA's interest in improving automobile safety, it is notable that they do not even suggest that the external benefits of automobile safety benefits could be large. To further our analysis, we contend that the contextual evidence suggests that an estimate of the external benefits of ADAS would not significantly increase its large, estimated benefits.

An implication of the fact that ADAS is a much stronger substitute for driver attention than other automobile safety features is that a large share of the overall benefits of ADAS is likely to be internalized by drivers. Indeed, our rough estimate that the external safety benefits of ADAS are on the order of 8.3% of the internal safety benefits of ADAS corroborates that claim. We also stress that our estimates of the effects of ADAS on fatal accidents include fatal accidents involving non-ADAS equipped vehicles, pedestrians, and cyclists because the dependent variable in our analysis is measured as the probability of a fatal accident resulting in a fatality involving any vehicle, pedestrian, or cyclist. As noted, the external benefits from fewer fatalities associated with those forms of transportation are likely to be a small fraction of the internal benefits to drivers of ADAS equipped vehicles. At the same time, the cost of fatal accidents greatly exceeds the cost of nonfatal accidents, so the external benefits of nonfatal accidents also are likely to be small. Finally, the scope of external benefits of ADAS is further limited because roughly one-third of all accidents and one-half of fatal accidents are single vehicle crashes while 5% of multivehicle accidents involve only vehicles that are equipped with ADAS.[27]

Consumers' Willingness to Pay for ADAS

Consumers' willingness to pay (WTP) for ADAS incorporates consumers' value of reducing the probability of dying in a crash, sustaining an injury in a crash, and having to bear the cost of repairing or replacing a vehicle involved in a crash. It is possible for us to use our results to quantify the first effect to provide suggestive evidence that based on their WTP for ADAS to

[27] Other potential external benefits of ADAS may be difficult to assess because they intersect with broader policy issues. For example, ADAS could reduce congestion because there would be fewer incident delays but those delays could and should be addressed by government implementing efficient congestion pricing, which could encourage motorists to adopt new technologies, such as WAZE, that could improve traffic flows.

reduce the probability of dying in a crash, consumers are reasonably well-informed about the effectiveness of ADAS and do not underestimate its safety benefits. To do so, we provide a rough estimate of consumers' WTP, which incorporates a plausible estimate of the value of life and the probability of a fatal crash and compare the estimated WTP with the cost of installing ADAS in a vehicle to determine if a market outcome is possible where consumers are willing to pay the cost of a safety technology whose benefits they accurately value.

We are not aware of any estimate in the literature of consumers' WTP for ADAS to reduce the probability of dying in a crash that we can use here. To obtain this WTP estimate requires one to collect a detailed data set to estimate a vehicle choice model that includes highly differentiated vehicle attributes down to the trim level. The data collection and estimation of such a vehicle choice model is beyond the scope of this paper and remains a topic for future research.

As a constructive alternative, we present a back-of-the-envelope estimate of WTP to advance the discussion. To begin, note that the probability of a person dying in a car crash during their lifetime is roughly 1.0%[28], with roughly 53% of fatalities occurring in single-vehicle crashes. Because we found ADAS reduced the probability of dying in a single-vehicle accident, we will focus on those accidents. If a person owns roughly six cars during their lifetime[29], the probability of dying in one of those cars in a single-vehicle crash is 0.088%. Based on our estimates in table 2, the probability of dying in those cars in a single-vehicle accident is reduced by 32%, or becomes 0.059%, if they are equipped with ADAS. Finally, consistent with US Department of Transportation Guidelines during our sample period, assume the value of life for a person is $6 million[30], which implies that a person would be willing to pay $60,000 to reduce the probability of dying in a fatal car accident by 1%. Thus, on average, motorists should be willing to pay roughly $1,800 (i.e., $60,000 · (0.088-0.059)) for ADAS to be installed in their vehicle.

We also are not aware of any econometric estimates of the marginal cost of installing ADAS in a range of different vehicles. However, industry evidence is available that suggests the average cost of installing basic ADAS features is $4,248.[31] Recall, our estimate of motorists' average WTP applies only to the lifesaving benefits of ADAS in single vehicle accidents and does not capture the two other significant benefits of ADAS, including reductions in the millions of annual injuries

[28] https://www.curcio-law.com/blog/odds-of-dying-in-a-car-crash/.
[29] https://www.usedvwaudi.com/blog/2017/11/16/how-many-cars-will-you-go-through-in-one-lifetime.
[30] https://www.theglobalist.com/the-cost-of-a-human-life-statistically-speaking/.
[31] https://www.sbdautomotive.com/post/collision-avoidance-saves-lives-vpp

from non-fatal accidents, which can notably decrease a person's productivity and quality of life, and reductions in vehicle repair or replacement costs, which can increase drivers' insurance rates. Motorists' inflated average WTP to account for those significant benefits would therefore greatly exceed $1,800 and would likely to be aligned with the $4248 average cost of installing basic ADAS features. Accordingly, we have cast credible doubt on the claim that a government mandate is justified on the grounds that motorists are not informed about the benefits of ADAS safety features.

Alternative calculations of motorists' average WTP, regardless of their relationship with average installation costs, underscore the fact that focusing on average WTP masks consumers' heterogeneity. For instance, older drivers may value ADAS more than prime-age drivers. Provided that older drivers have access to ADAS technology, it is questionable whether prime-age drivers who don't particularly value ADAS should be cross-subsidizing them. Importantly, it also masks automakers' interest in catering to consumers' evolving heterogeneous preferences for ADAS safety features by gradually increasing their availability on more vehicles and by pricing them in a manner that is consistent with their safety benefits, installation costs, and consumers' WTP.

Equity Considerations and Supply-Side Constraints

The remaining justification for mandating the installation of ADAS for all automobiles and light trucks is that equitable access to them is limited by supply-side constraints. Specifically, at a cost of nearly $5,000, ADAS may raise distributional concerns that only affluent households can afford the types of vehicles that offer the technology. This justification is inconsistent with the evidence presented in figure 1 that automakers have significantly increased the availability of ADAS on a greater share of new vehicles over time and are expected to continue to do so. We also show in figure 8 that the supports of the distributions of manufacturers' suggested retail prices for all ADAS equipped and non-ADAS equipped vehicles in 2019 are nearly identical, indicating that ADAS is generally available at all price points for new vehicles, and that consumers can choose from either ADAS equipped or non-ADAS equipped vehicles at all price points.

Given the availability of ADAS in less expensive cars, less-affluent households who value ADAS can trade off other amenities to purchase it. However, a government mandate requiring automakers to install ADAS in all their new vehicles will not ameliorate distributional concerns. Instead, it will expand the share of new cars that less affluent drivers may find too expensive to purchase.

Finally, it is important to realize that any government action that seeks to expand the adoption of ADAS by the entire US vehicle fleet would not be accomplished in a short period of time. Instead, it would take decades for used vehicles that are not equipped with ADAS to be scrapped and for new vehicles that are equipped with ADAS and that meet the government's performance standards to fully comprise the vehicle fleet. For example, Alarfaj, Griffin, and Samaras (2020) report that it would take three decades and possibly four to retire the current light duty vehicle stock.

Consider the time it will take for the less ambitious but still challenging goal of requiring automatic emergency braking to be installed in all new 2030 model vehicles to have a positive effect on safety. All current vehicles with AEB will have to install AEB that meets the higher government standards. All new vehicles must install AEB that meets the government standards. As a result, the fleet will be comprised of a majority share of vehicles without AEB for as long as those vehicles are on the road and of a smaller but growing share of vehicles with AEB that meets the government's standards. The mix of vehicles with and without AEB will gradually improve, but it will take considerable time for the government's mandate that AEB must be installed in all new 2030 models to improve automobile safety sufficiently for the improvement to be detected in a time-series analysis of automobile accidents and fatalities.

7. Conclusion

Historically, automakers' introduction of a new safety feature has spurred controversy over its effectiveness at reducing the probability of fatal and severe injuries, accounting for drivers' behavior in response to the safety feature. After a safety feature has proved to be effective, policymakers have often considered whether automakers should be required to install it in all their new vehicles.

We have addressed the first issue empirically in the context of automakers' introduction of ADAS safety features. We have presented causal evidence that ADAS has improved automobile safety by significantly reducing the probability of motorists being involved in fatal and nonfatal accidents, accounting for the change in drivers' behavior in response to the installation of those safety features in their vehicle. We also have tested for the possibility that our finding could be compromised by selectivity bias that could appear in multiple contexts and we have consistently rejected that possibility.

Our finding that ADAS has improved automobile safety is particularly important because it provides early evidence of some of the benefits of vehicle automation in actual travel environments.[32] We hope that our finding spurs greater interest in the development and widespread adoption of fully autonomous vehicles and in the potential benefits of other AI transportation technologies (Winston and Karpilow (2020), Winston, Yan, and Associates (2024))

Turning to the second issue, government's role in the adoption of automobile safety features has not historically been informed by a careful assessment of the costs and benefits of their intervention. For example, Mannering and Winston (1995) found that, on average, motorists were willing to pay the average cost of installing air bags in their vehicles and that automakers were steadily installing airbags on those vehicles for which motorists were willing to pay the average cost of air bag installation. Nonetheless, in 1998, federal law required that all cars and light trucks sold in the United States have air bags on both sides of the front seat without carefully assessing whether such a requirement was justified on cost-benefit grounds, accounting for the welfare loss to motorists who valued air bags at less than the cost that was passed through in higher vehicle prices.

The speed with which ADAS safety features have been adopted is notable and our findings strongly indicate that motorists have benefited from their effectiveness. At the same time, our analysis casts doubt that government's intervention in the market's adoption of ADAS by mandating them for all vehicles would enhance social welfare. In fact, its recent rule requiring automakers to install emergency automatic braking on all new 2030 vehicles appears to be premature. Because the market for AI safety technologies is still in the early stage of its development, it is important for policymakers to be fully aware of the benefits from the market forces underlying consumers' voluntary adoption of these technologies before making any interventions that might turn out to reduce welfare.

[32] In the future, when the vehicle capital stock has turned over sufficiently to be comprised of a large share of ADAS-equipped vehicles, it would be useful to estimate the effect of the staggered adoption of ADAS-equipped vehicles on the nation's automobile fatalities and insurance costs. The latter will reflect a tradeoff between the lower claims caused by ADAS's reduction in accidents and the higher claims caused by ADAS's increase in the cost of a car and repairs.

Appendix A. Summary of the Data

As noted, we constructed a data set to analyze the effects of ADAS on all automobile accidents that occurred in Texas from 2010 to 2018 by combining information from three main sources: 1) all registered vehicles from the Texas Department of Transportation, 2) police accident reports from the Texas Department of Public Safety, and 3) trim level vehicle attributes from leading vehicle data aggregators. The main challenge to constructing our data set is to link the data from all three sources to identify whether ADAS safety technology is available on each vehicle registered in Texas.

The registration data contain the Vehicle Identification Number (VIN) of registered vehicles in Texas for the years 2010-2018. The VINs account for all in-state vehicles that were on the road during our sample period. Importantly, we are able to observe *all* the vehicles that were equipped with ADAS safety features in a given calendar year, regardless of whether they were involved in an accident.

The Texas police accident reports record all single and multi-vehicle auto accidents in the state of Texas involving motorists and pedestrians for the years 2010-2018. Importantly, these accident reports also include the VIN of all in-state and out of state vehicles involved in each accident, as well as accident severity, which ranges from vehicle damage only to fatalities. Because we have no information on out of state vehicles that were not involved in an accident, our initial estimates included only in-state vehicles involved in accidents. We then performed a sensitivity analysis including in-state and out of state vehicles in accidents in Texas.

We obtained vehicle attributes down to the trim level by web scraping multiple leading vehicle data aggregators, including TrueCar, Inc., MotorTrend, and Kelly Blue Book. The attributes data are at the detailed model year-make-model-trim level, which enables us to identify the specific safety features of a vehicle that vary at both the model year and the trim level.

To the link the data from the three sources, we proceeded as follows. First, for a given VIN in the registration data, we used a commercially available VIN decoder to obtain a string that describes its model year, make, model, and trim (henceforth nameplate).[33] Given the large number of registered VINs, simply decoding one-by-one was prohibitively time consuming.[34] Although manufacturers have a certain level of flexibility in terms of what information is encoded in their VINs, the make and model year of a VIN is always encoded in the first three and the tenth digit, respectively.[35] We therefore took a representative sample of more than two million VINs weighted by make and model year for decoding. After successfully decoding this sample of VINs and

[33] We should point out that not all VIN decoders can decode a VIN to the trim level; most can decode only to the model year-make-model level. For example, NHTSA provides a free VIN decoder that does not decode to the trim level. See https://www.nhtsa.gov/vin-decoder.

[34] Decoding the entire registration data would take years.

[35] See https://www.federalregister.gov/documents/2022/03/09/2022-04030/vehicle-identification-number-vin-requirements-manufacturer-identification-certification-replica.

obtaining their nameplate, we trained a random forest model to classify the remaining VINs.[36] This process allowed us to identify the nameplate of each VIN in our registration data.[37]

Second, the vehicle attributes data contain detailed information on all the features available for a given nameplate, including the safety related features of interest. We provide a summary of the trim level features we were able to obtain, including both safety and non-safety related features, at the end of this appendix. ADAS safety features, however, are marketed under various names by different auto manufacturers with no standardization. For example, Adaptive Cruise Control is called "Intelligent Cruise Control" by Nissan and "Radar Cruise Control with Stop and Go" by Mazda, even though both correspond to the same underlying technology. We therefore used various string manipulation techniques coupled with manual inspection to correctly identify each ADAS safety feature for a given nameplate.

Third, although the decoder provides a nameplate string for a given VIN, this string rarely matches the string we were able to obtain from the wed scraped vehicle attributes data, which prohibits a direct merge. For example, the VIN "5J8YD4H05LL024902" is decoded as "2020, Acura, MDX, A-SPEC." Its counterpart in the attributes data is "2020 Acura MDX Technology and A-Spec Package," even though they represent the same nameplate. We therefore used fuzzy string match techniques to link the two nameplates. This process allowed us to identify whether ADAS safety technology was available for each VIN in our sample.[38]

Lastly, because the availability of ADAS safety technology varies at both the model year and trim level, we aggregate nameplates to the trim and the first model year that it received ADAS. That is, for each vehicle make-model (denoted i), we define vehicle type (denoted j) as a combination of trim and the first model year in which ADAS became available. Specifically, for each type j, we aggregate all trims of this type by taking averages of other attributes (such as MSRP). Using the example in Table 1, all Acura MDX trims that began to receive ADAS in model year 2015 are aggregated into the "high" trim; all MDX trims that began to receive ADAS in model year 2018 but not before are aggregated into the "medium" trim; and the remaining MDX trims that never received ADAS are aggregated into the "low" trim.[39] In the end, our data construction process resulted in 6,268 unique vehicle types (i.e., aggregated trims) that vary at the yij level. This allowed us to define our treatment variable, the availability of ADAS (denote by the dummy variable S_{yij}) to also vary at the yij level. Specifically, for vehicle type yij, S_{yij} has value 1 if the aggregated trim j received ADAS in model year $y;$ 0 otherwise.

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[36] We also experimented with other algorithms such as Decision Tree and Naïve Bayes. Random Forest was our preferred algorithm given its robustness to overfitting and our large sample size. To further reduce computational complexity in this process, we drop the last six digits of each VIN, which only contains a vehicle's serial number.
[37] We also filtered out VINs that either have model years older than 2000 or pertain to irrelevant vehicle categories, such as motorcycles and heavy-duty trailer trucks.
[38] The VIN decoder also provides attribute information, such as MSRP, body type, fuel type. We cross-checked attributes from both the decoder and our web scraped data and found that they generally agreed for each nameplate.
[39] Once a trim receives ADAS in a model year, it continues to have ADAS in all subsequent model years. This process results in three distinct groups of Acura MDX trims, each with a unique set of aggregated attributes.

Appendix B. Summary of Non-ADAS and Non-Safety Related Trim Features

The non-ADAS and non-safety related trim features that were available for vehicles with high trim, but not for vehicles with low trim are as follows:

Non-ADAS Vehicle Safety Features

Rear and side view with simulated aerial camera

360 Degree Surround Camera
Panoramic View Monitor

Digital Backup Sensors

Active Blind Spot w/Front Park Sensor
Adaptive Light Control
Auto-Dimming Rearview Mirror
Bi-Xenon Cornering Headlights
Black Out LED Daytime Running Lights
Enhanced Active Park Assist w/Forward Sensing System
Inflatable Rear-Seatbelts
Night View Assist PLUS w/Pedestrian Detection
Side Curtain and Seat Mounted Side Impact Airbags
Trailer Tow Camera System
Heated Sideview Mirrors

Non-Safety Related Trim Features

Rear power outlet(s)

Cargo area power outlet(s)

Anti-Theft Alarm System w/Immobilizer
Intrusion Sensor

Heated Windshield Washer Reservoir (SPC)
Keyless Entry w/Hands-Free Tailgate Opening
Headlamp Washers

Premium Leather Collection

Heated Rear Seats

Appendix C. A Suggestive Calculation of ADAS Externalities

In this appendix, we propose a suggestive but instructive approach to formally measuring the externalities of ADAS using only observational data. Doing so requires certain additional assumptions that are not necessary for our main analysis. First, we restrict our attention only to multi-vehicle accidents, which is appropriate given the assumption that generally there are no direct spillovers in single vehicle accidents. Of course, other spillovers, such as congestion caused by rubbernecking following a crash, may occur. Second, we assume for simplicity that all multi-vehicle accidents involve exactly two vehicles.

Denote a vehicle of type x as either being never treated ($x = 0$) or treated at some point ($x = 1$) and assume there are N_x vehicles of type x on the road. Let s^{xy} be the probability a vehicle of type x encounters a vehicle of type y on the road (e.g., $s^{01} = \Pr[\text{never treated vehicle encounters an eventually treated vehicle}]$. Similarly, let p^{xy} be the probability that a vehicle of type x gets in an accident with a vehicle of type y conditional on the vehicles encountering each other on the road. Finally, let n_x be the number of accidents involving a vehicle of type x.

If we estimated the accident equation

$$A_{yijt} = \beta\, S_{yijt} + \lambda_{ijt} + \lambda_{iyt} + \epsilon_{yijt}, \qquad \text{(A1)}$$

which is the OLS analog to the Poisson regression equation (1) on a subsample of multi-vehicle accidents, then we could express the parameter of interest β as

$$\beta = E[n_1 - n_0]_{\text{after 1 is treated}} - E[n_1 - n_0]_{\text{before 1 is treated}} \qquad \text{(A2)}$$

Under the assumption that N_x and s^{xy} are unchanged before and after vehicles get treated, then all of the observed relative changes in accidents encapsulated in β can be attributed to changes in vehicle safety (i.e., p^{xy}). This allows us to decompose equation (A2) as follows:

$$\begin{aligned}\beta &= [N_1 p^{11} s^{11} + N_1 p^{01} s^{01} - N_0 p^{01} s^{10} - N_0 p^{00} s^{00}] \\ &\quad - [N_1 p^{00} s^{11} + N_1 p^{00} s^{01} - N_0 p^{00} s^{10} - N_0 p^{00} s^{00}]. \qquad \text{(A3)}\end{aligned}$$

Note that all of the conditional accident probabilities in the second term are set to p^{00} because no vehicles are treated. The expression in equation (A3) can be further simplified to:

$$\beta = \underbrace{N_1 s^{11}(p^{11} - p^{00}) + N_1 s^{10}(p^{01} - p^{00})}_{\text{Total Internal Effect}} - \underbrace{N_0 s^{01}(p^{01} - p^{00})}_{\text{Spillover Effect}} \qquad \text{(A4)}$$

The first term of the total internal effect in equation (6) corresponds to the effect of ADAS in accidents when both vehicles are treated, and the second term of the total internal effect corresponds to the effect of ADAS in accidents when only one vehicle is treated. Together they comprise the total internal effect of ADAS. Meanwhile, the third term corresponds to the spillover effect of ADAS on vehicles that are never treated. Hence our empirical strategy identifies the total internal effect of ADAS net of the externality.

This decomposition exercise suggests a straightforward approach to estimate the size of the spillover. First, we obtain β by estimating equation (A1) with all multivehicle accidents on the left hand side. Second, we obtain the first term of equation (A4) by estimating equation (A1) with only multivehicle accidents in which both vehicles' trims are eventually treated on the left hand side. Third, we obtain the second term of equation (A4) by estimating equation (A1) with only multivehicle accidents in which one vehicle's trim is eventually treated on the left hand side. The spillover effect can then be computed by simply subtracting the first result from the second and third results.

In Figure 9, we present the results of this decomposition for accidents overall and disaggregated by time of day, vehicle speed, and road and travel conditions.[40] We find that spillovers tend be larger during darkness and on poor road surfaces, which is consistent with ADAS being a substitute for driver attention. This point is reinforced for especially dangerous driving environments by our finding that the spillover effects of ADAS increase as the speed at which an accident occurred increases, with a peak spillover effect at speeds of 75mph or greater. We also find that the spillover effect of ADAS for accidents overall is equal to only 8.3% of the total internal effect of ADAS or a little less than one percentage point of our estimated 10% decrease in total accidents attributable to ADAS. Accordingly, we conclude that the bias due to contamination is unlikely to affect our results in an economically meaningful way.

[40] We were unable to perform the decomposition exercise for fatal accidents because splitting the dependent variable in order to estimate the total internal effect reduced the already low variation in fatal accidents by too much.

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Table 1. Example of the Data Structure for the Acura MDX

Treated Vehicles			2015 H	2015-2016 H	2015-2017 H	2018 M 2015-2018 H	2018-2019 M 2015-2019 H
Untreated Vehicles	2000-2013 L 2000-2013 M 2000-2013 H	2000-2014 L 2000-2014 M 2000-2014 H	2000-2015 L 2000-2015 M 2000-2014 H	2000-2016 L 2000-2016 M 2000-2014 H	2000-2017 L 2000-2017 M 2000-2014 H	2000-2018 L 2000-2017 M 2000-2014 H	2000-2019 L 2000-2017 M 2000-2014 H
Calendar Year	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**

Notes: There are three trim levels for the MDX: L, M and H. Trim level H received ADAS safety features in model year 2015. Trim level M received ADAS safety features in 2018.

Table 2. Effects of ADAS on Accidents and Fatalities

Dependent Variable	All Accidents		Fatal Accidents	
	Single Veh.	Multi Veh.	Single Veh.	Multi Veh.
	(1)	(2)	(3)	(4)
ADAS Safety Features Dummy	0.87***	0.90**	0.68**	0.98
	(0.05)	(0.04)	(0.13)	(0.13)
Make-Model-Trim-Calendar Year (ijt) FEs?	Y	Y	Y	Y
Make-Model-Model Year-Calendar Year (yt) FEs?	Y	Y	Y	Y
Pseudo R-squared	0.76	0.87	0.21	0.24
Number of observations	4,776	4,983	1,643	2,315

Notes: Incidence Risk Ratios are presented from Poisson maximum likelihood regressions with heteroskedasticity robust standard errors clustered by model year-make-model presented in parentheses. Vehicle trims that are never equipped with ADAS are excluded. *** 99% significance, ** 95% significance, * 90% significance.

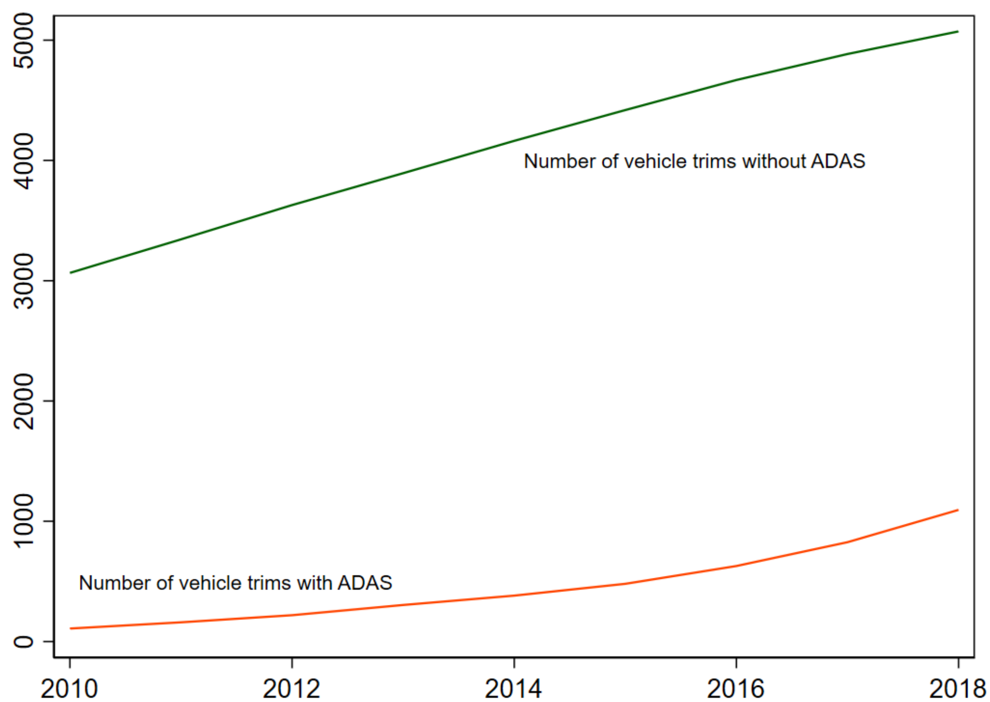
Table 3. Effects of ADAS on Driving

Dependent Variable	VMT	log(VMT)
	(1)	(2)
ADAS Safety Features Dummy	-31.56	0.04
	(138.07)	(0.04)
Make-Model-Trim-Calendar Year (ijt) FEs?	Y	Y
Make-Model-Model Year-Calendar Year (yt) FEs?	Y	Y
Pseudo R-squared	0.74	0.77
Number of observations	6,565	6,464

Notes: Heteroskedasticity robust standard errors clustered by model year-make-model presented in parentheses. Vehicle trims that are never equipped with ADAS are excluded. For registrations, vehicles in their first*** 99% significance, ** 95% significance, * 90% significance.

Figure 1. Evolution of the Rollout of ADAS

Panel A: Number of Unique Vehicle Trims over Time



Panel B: Share of ADAS Equipped Vehicles over Time

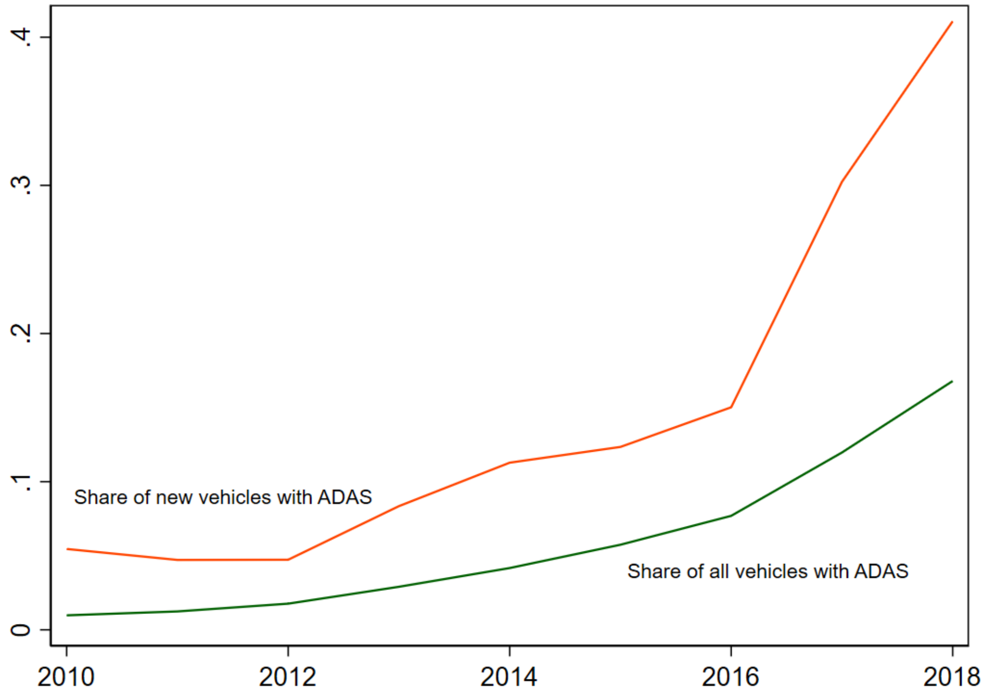


Figure 2. Overview of the Data Construction

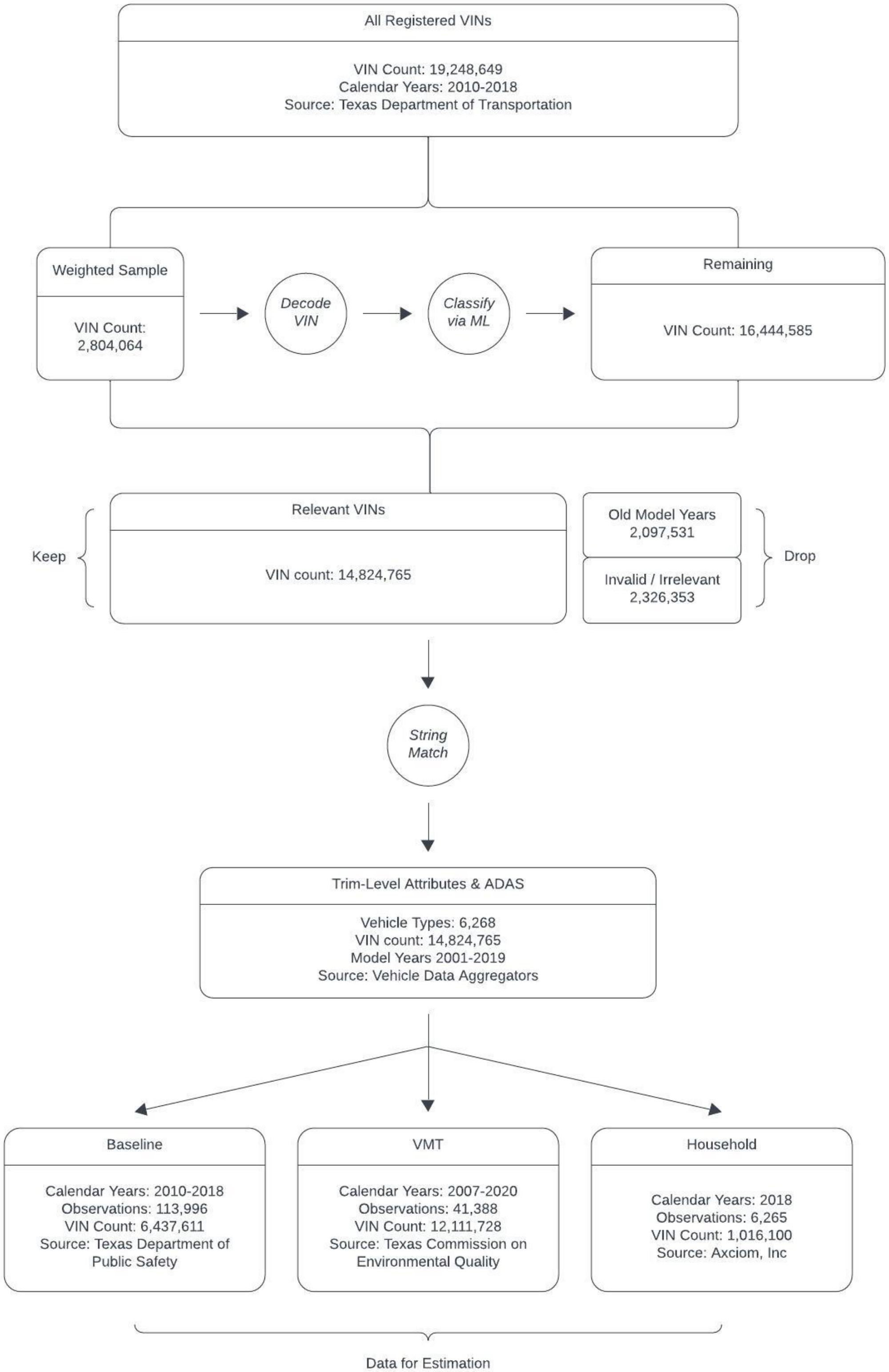
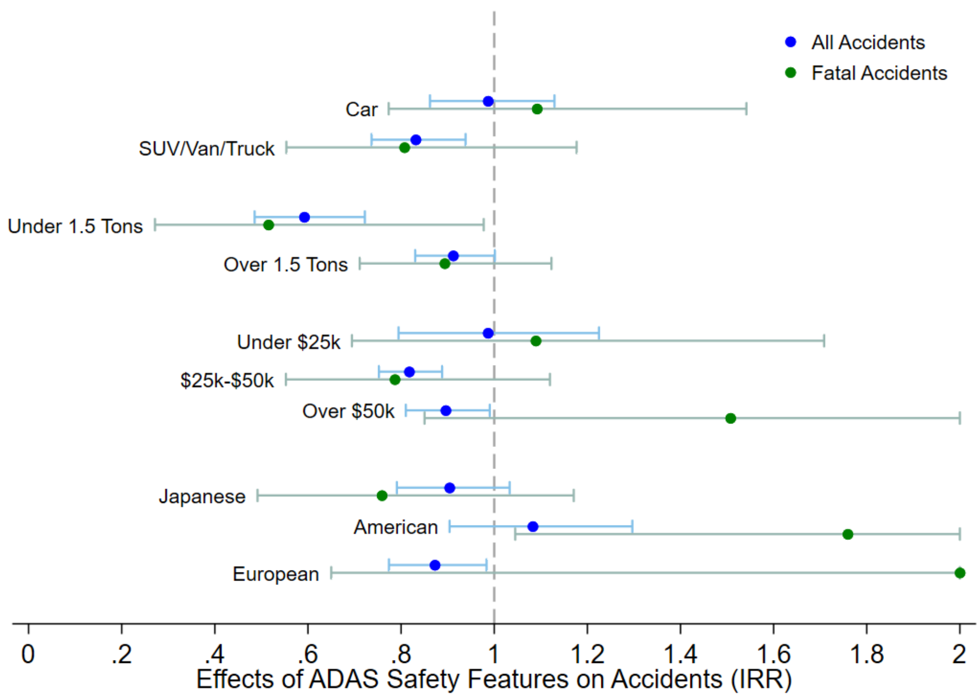
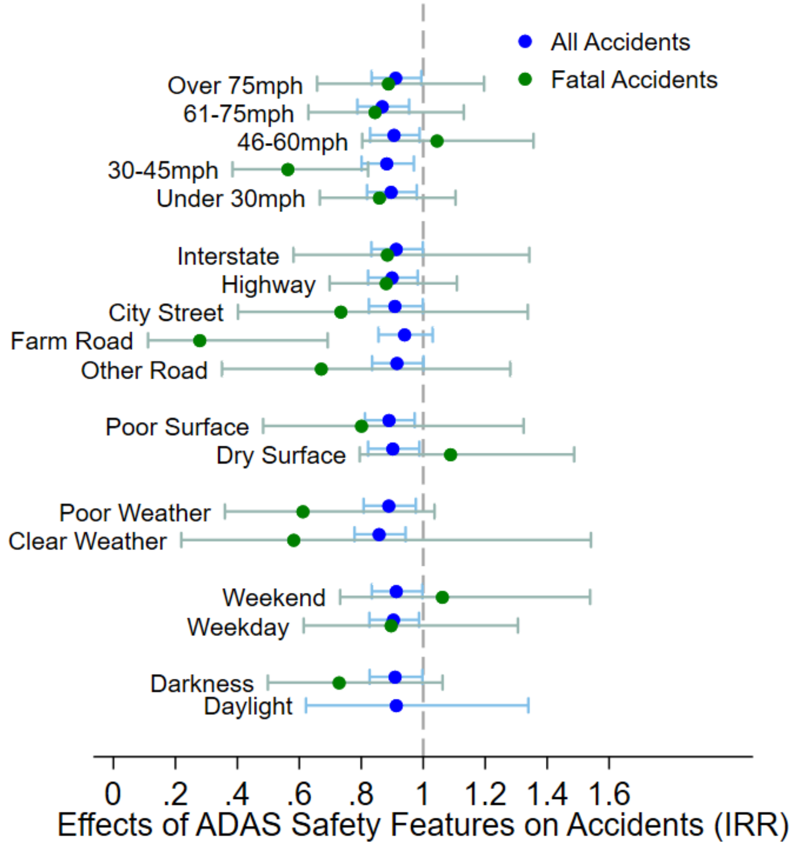


Figure 3. Heterogeneous Effects of ADAS Safety Features on Accident Rate by Vehicle Type



Note: Incidence Risk Ratios are presented from Poisson maximum likelihood regressions with 95% confidence intervals formed form heteroskedasticity robust standard errors clustered by model year-make-model. Parameter estimates and confidence intervals are truncated at 2 for clarity.

Figure 4. Heterogeneous Effects of ADAS Safety Features on Accident Rate by Accident Conditions



Note: Incidence Risk Ratios are presented from Poisson maximum likelihood regressions with 95% confidence intervals formed form heteroskedasticity robust standard errors clustered by model year-make-model.

Figure 5. Event Study Style Plot of the Effects of ADAS

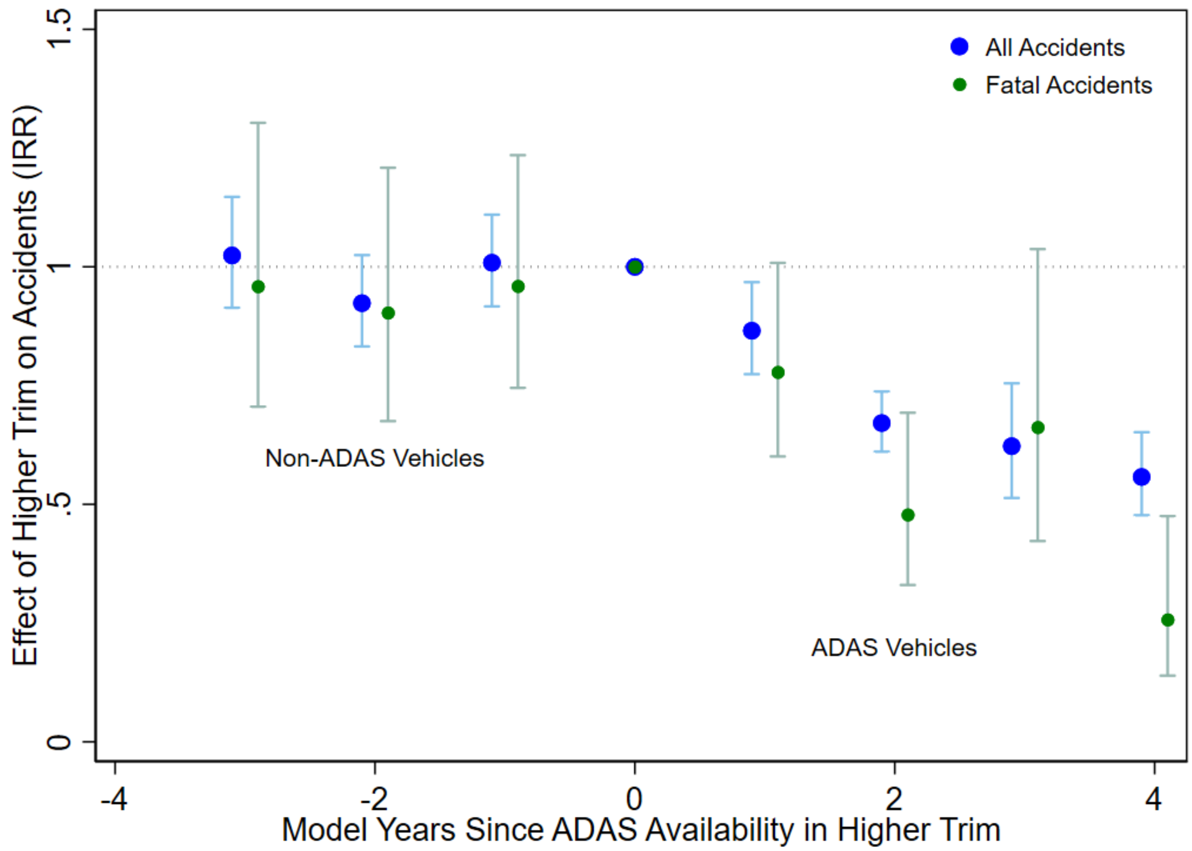
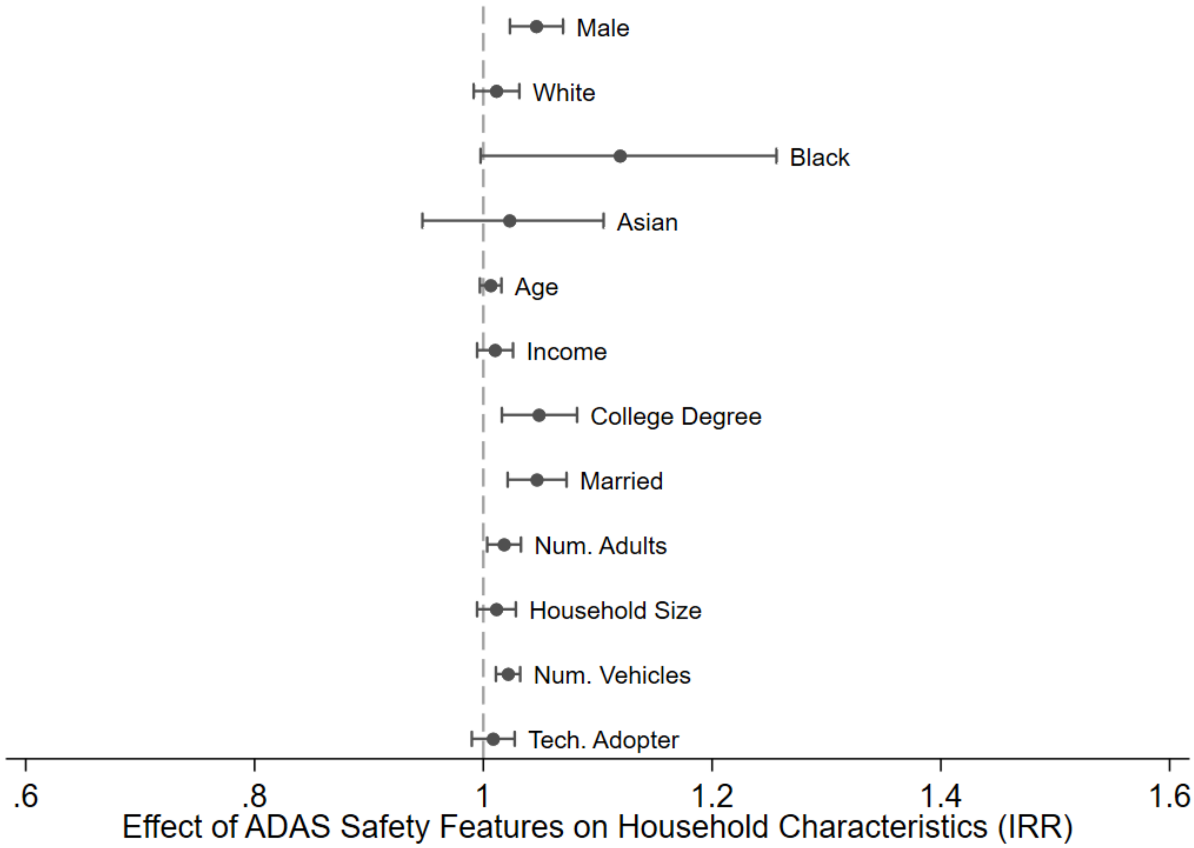
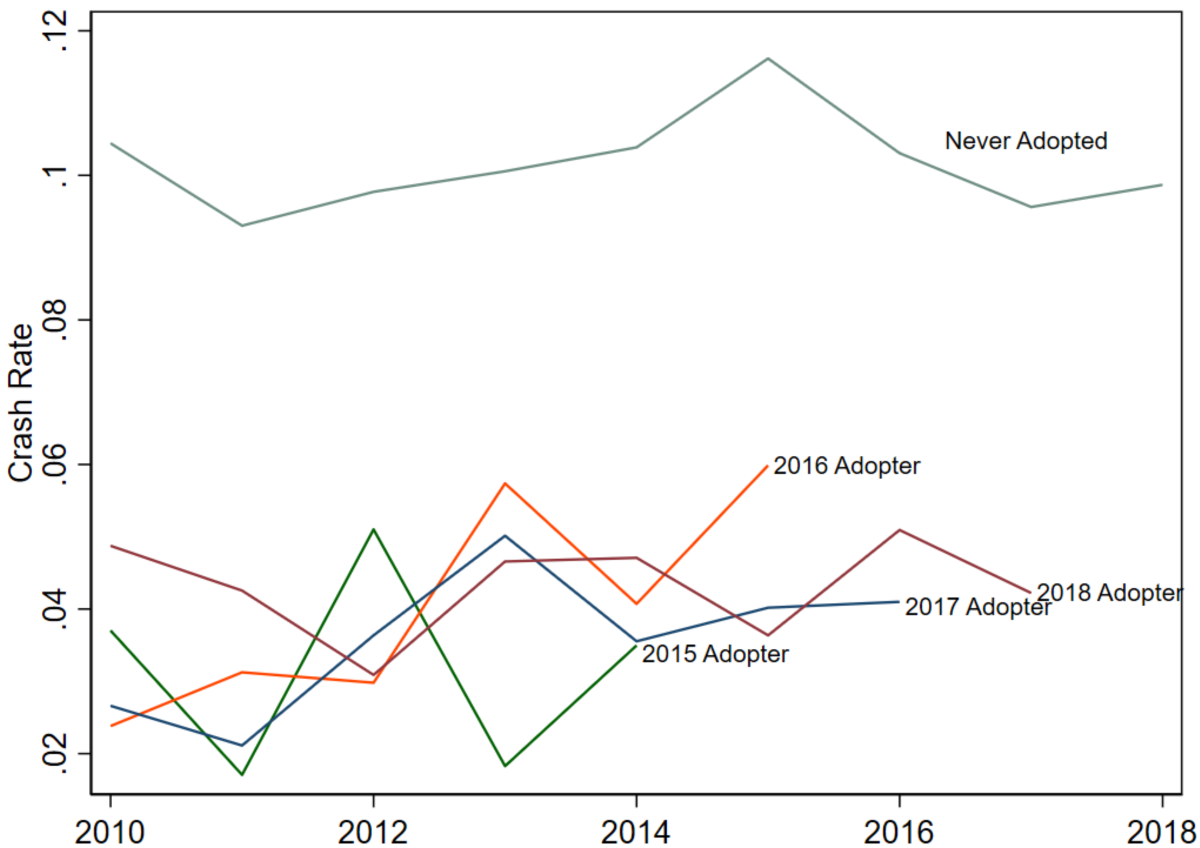


Figure 6. Effects of ADAS by Household Characteristics (IRR)



Note: Incidence Risk Ratios are presented from Poisson maximum likelihood regressions with 95% confidence intervals formed form heteroskedasticity robust standard errors clustered by model year-make-model.

Figure 7. Crash Rate over Time by Household ADAS Adoption Year



Notes: This figure shows the evolution of crash rates of households over time split up by when each household first adopted an ADAS enabled vehicle.

Figure 8. Empirical Distributions of Prices for Vehicles With and Without ADAS Safety Features

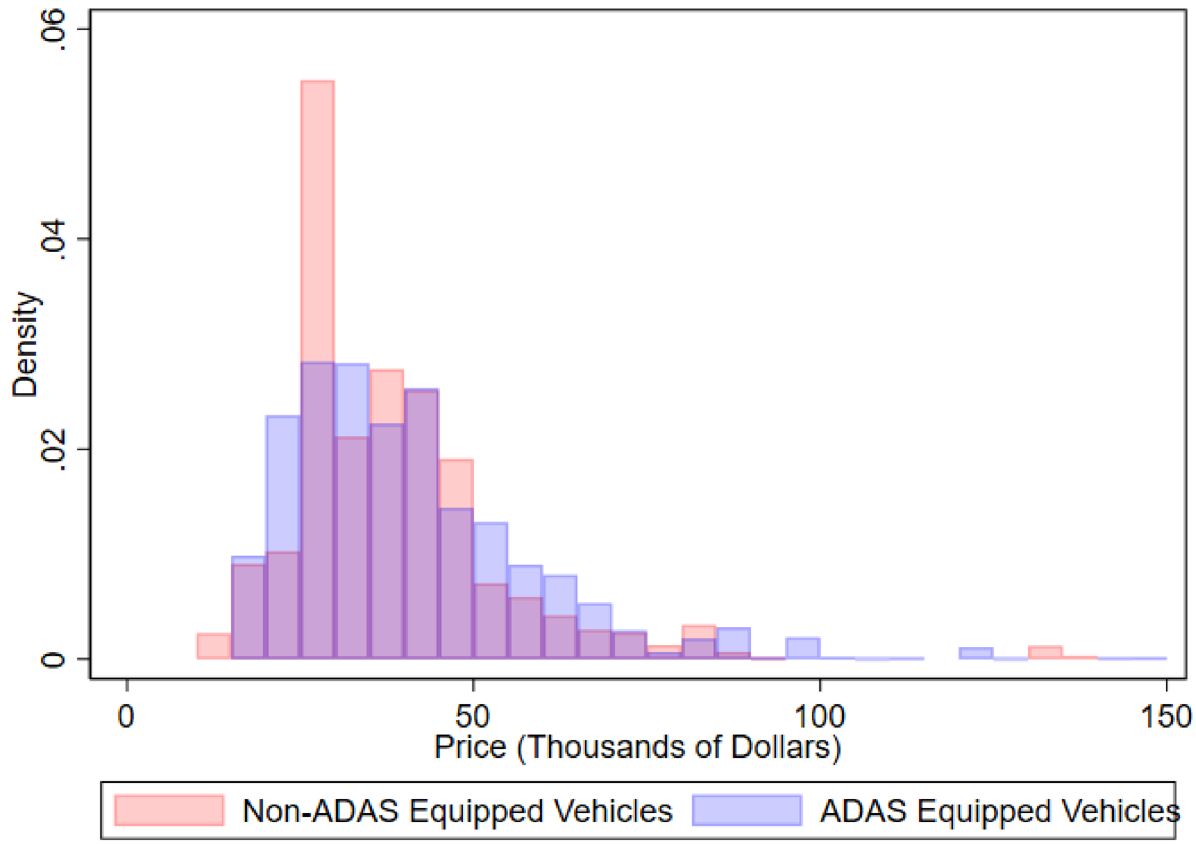
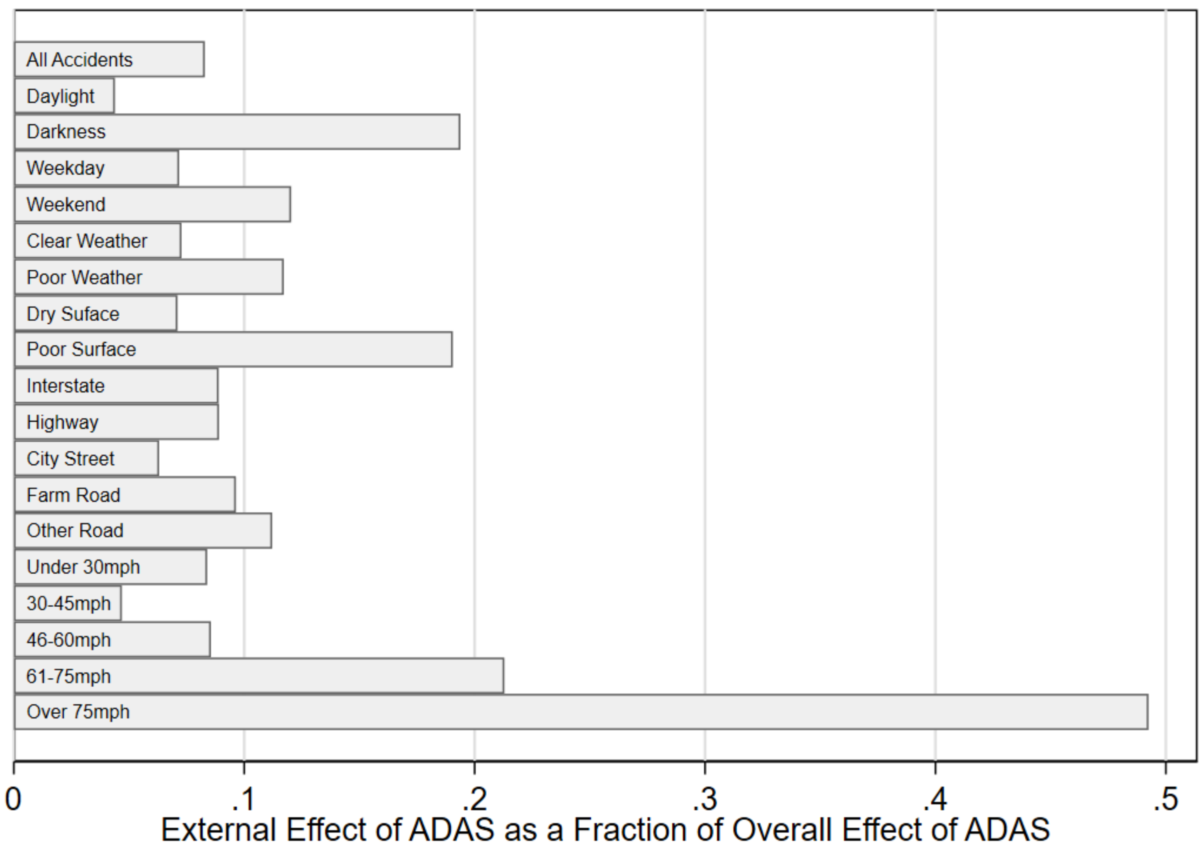


Figure 9. External Effects of ADAS



Note: External effects are calculated as described in the text and expressed as a ratio of the overall estimated effect. For example, we estimate external benefits of ADAS for all accident types to equal roughly 8.3% of the total effect of ADAS as presented in Table 1.