The Effect of Vehicle Size on Pedestrian Death Risk

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July 5, 2023

Abstract

Pedestrian deaths in the US have risen in recent years. In 2021, 7,400 pedestrians were killed in vehicle crashes. Concurrently, the cars driven on US roads have increased in size, as consumers opt for larger and heavier light trucks rather than cars. Increased vehicle size may pose a safety risk for pedestrians. I merge US crash data with a public Canadian regulatory data set on vehicle dimensions and weights to test for the impact of vehicle size on the likelihood that a struck pedestrian dies. I find larger vehicles, particularly large SUVs and pickup trucks, are more dangerous for pedestrians. After controlling for crash characteristics, I estimate a pedestrian is 70% more likely to die in a collision if the involved vehicle is a pickup truck rather than a car, and death is twice as likely if the vehicle is a large SUV rather than a car. I also find marginal increases in vehicle weight and height are associated with significantly higher fatality risk. A 10 cm increase in the vehicle's front-end height is associated with a 22% increase in fatality risk. I estimate that light trucks caused roughly 1,000 additional pedestrian deaths in the US in 2021 due to their size relative to cars.

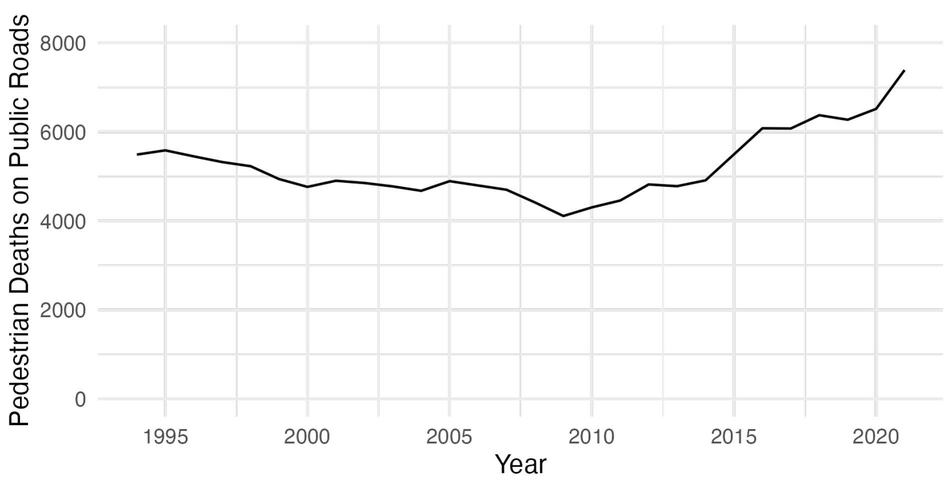
Transportation; Safety; Health; Traffic fatalities; Externalities

I1; R41; R42; R48

1 Introduction

The number of pedestrians killed in vehicle crashes in the US has risen dramatically. Between 2010 and 2021 the number of pedestrians killed annually in collisions increased by 72%, from 4,300 to 7,400 (Figure 1). Since 2000, over 110,000 pedestrians have died. The increase in US pedestrian deaths has occurred during a period when US motorist deaths have been falling. One plausible explanation for the increase in US pedestrian deaths is the increasing size of vehicles. Light trucks, a class of vehicles that includes SUVs, pickups, and vans, have surged in popularity. In 2021, 78% of new passenger vehicles sold or leased in the US were light trucks rather than cars.[1] Larger vehicles may be more dangerous for pedestrians due to their greater crash impact force, higher front-end designs, and larger driver blind spots.

Figure 1: Pedestrian Deaths per Year in the US



After falling significantly during the 1990s and early 2000s, pedestrian deaths began increasing. For the decade spanning 2011-2021, annual pedestrian deaths increased 66%, with 7,400 deaths recorded in 2021. Data Source: Fatality Analysis Reporting System (FARS)

This paper will analyze national data on 3,400 vehicle crashes where a pedestrian was struck, and estimate the partial effect vehicle type and size has on the pedestrian survival probability. By merging a database of crashes onto a database of physical vehicle dimensions I directly estimate the effect of vehicle size on pedestrian outcomes.

[1] Bureau of Transportation Statistics. New and Used Passenger Car and Light Truck Sales and Leases. 2021.

Extensive information on crash characteristics allows me to control for the effect of differing crash scenarios. Results demonstrate larger vehicles are more likely to kill pedestrians, conditional on striking them. I find that full-size SUVs and pickup trucks pose a particular danger to pedestrians, substantially raising their probability of death. While some past studies have used vehicle body type (i.e. light truck vs car) as a proxy for size, this is the first study to combine vehicle-level dimension measurements with real-world crash-level data to estimate the partial effect of vehicle size on pedestrian death probability. I am able to measure front-end vehicle height specifically, which has often been argued to be the mechanism relating vehicle size to higher pedestrian death risk.

Several prior economic studies have examined the relationship between vehicle size and road safety. The majority of past studies have focused on motorist safety but included some analysis of pedestrian risk. Crandall and Graham (1989) argued that federal vehicle mileage standards would encourage smaller vehicles in the US, and lead to more road fatalities due to smaller cars providing less protection for their occupants. However, the analysis in Crandall and Graham (1989) generally ignored the external impact of vehicle size on other road users. Subsequent studies have incorporated the issue of external safety effects. Using US crash data from 1995-2001, White (2004) found that larger vehicles were creating more dangerous road conditions in aggregate. The study estimated that for every life saved by an individual switching from a car to a light truck, 4.3 fatalities occurred among other drivers, pedestrians, and cyclists. Anderson (2008) examined state-level panel data on vehicle size and crashes in the US from 1980-2004, finding states with more light trucks had higher rates of traffic fatalities, with increased deaths among drivers of smaller vehicles, and pedestrians. Li (2012) as well as Anderson and Auffhammer (2014) both examined US police report data on vehicle crashes and merged on vehicle weight information by using the unique Vehicle Identification Number (VIN) attached to each vehicle in the police report. Both studies reached an identical conclusion; that a 100 kg increase in a vehicle's weight increased the probability of death in a vehicle it strikes by 10%. Van Ommeren et al. (2013) performed a similar analysis with data from the Netherlands, finding a 100 kg increase in vehicle weight resulted in a 14% increase in the probability of a fatality occurring in the opposing car.

White (2004), Li (2012), and Anderson and Auffhammer (2014) all characterize the growth in US vehicle size as an "arms race." As the external safety risk of vehicles increases with size, individual drivers can act to protect themselves from these externalities by purchasing larger vehicles themselves. In this way, individual incentives may lead to a sub-optimal equilibrium where drivers select vehicles that improve their own safety, but lower societal safety. The continued growth in vehicle size after the publication of these papers suggests that the so-called arms race has continued. Pedestrians are unable to participate in this arms race, which could be contributing to the rising rate of pedestrian deaths relative to vehicle occupant deaths. While these prior studies examine the effect of vehicle size on road safety, they are primarily focused on motorists rather than pedestrians.

In research closely related to the current study, Lefler and Gabler (2004) analyzed US pedestrian crashes during the 1990s, concluding that pedestrians hit by a light truck rather than a car are two to three times more likely to die. Ballesteros et al. (2004) analyzed pedestrian data from Maryland in the late 1990s, finding light trucks doubled the odds of a pedestrian suffering a traumatic injury compared to cars, with the relationship most pronounced for lower-speed collisions. Roudsari et al. (2004) used US data from 1994-1998 and estimated that, after controlling for crash characteristics and victim demographics, light trucks were more than three times as likely to cause the pedestrian to die compared to cars. A summary of other past research is provided in Desapriya et al. (2010), including a meta-analysis of findings. The authors conclude that pedestrians are roughly 50% more likely to die when struck by a light truck rather than a car, based on all prior research.

Given the significant shift in vehicle size and pedestrian death frequency in recent years, the prior studies, which primarily use data from the 1990s, may be an imperfect guide to current conditions. Two more recent studies examine vehicle size and pedestrian death risk. Tyndall (2021) compared changing vehicle fleets and pedestrian deaths across US metropolitan areas between 2001-2019. The size of vehicles hitting pedestrians over this time-period rose dramatically and the metropolitan areas with the largest increases in vehicle size also saw the largest rise in pedestrian deaths. The paper estimated that replacing all light trucks with cars would have reduced annual pedestrian deaths by 460 during 2019. Edwards and Leonard (2022) examined both crash and hospital record data in Chicago finding that while pickups were involved in 6% of pedestrian crashes, they were involved in 13% of fatal pedestrian crashes. SUVs were involved in 15% of pedestrian crashes, but 25% of fatal pedestrian crashes. Using hospital records, the authors examine the intensive margin among surviving pedestrians, finding those struck by larger vehicles had more serious injuries as captured by higher hospital bills.

Curb weight, the weight of a vehicle with standard features and gas but no passengers or cargo, has been used in some past studies as the measure of vehicle size because it is available in some data sets. In terms of the physics of a collision, it is not completely clear that vehicle weight per se is important to pedestrian safety. The ratio of a vehicle's weight to a person's weight is large. Therefore, a marginal increase in a vehicle's weight might only have a small effect on the amount of kinetic energy transferred from the vehicle to a person's body.[2] However, the dimensions of the vehicle's front-end could have dramatic effects on the physics of the collision from the pedestrian's perspective.

Pedestrians may be particularly vulnerable to changing vehicle heights as the high front-ends of large vehicles mean the point of first contact in a collision with a pedestrian is more likely to be in the torso or head, rather than the legs. Vehicles with higher front-ends are also more likely to push the pedestrian under the vehicle rather than deflecting them onto the hood. Tamura et al. (2008) used simulated crash data to model brain trauma, finding an SUV traveling at 40 km/h would impart twice the impact force on the brain as a sedan traveling at the same speed. Simms and Wood (2006) also used simulated crash data and concluded that SUVs are significantly more hazardous in pedestrian collisions due to their higher front-ends. Numerous other simulation exercises of pedestrian crashes have concluded that large vehicles are more dangerous for pedestrians (Crocetta et al., 2015; Li et al., 2017; Yin et al., 2017).

This paper makes a number of specific contributions to the literature. First, it analyzes national, crash-level data covering recent vehicle-pedestrian crashes. Second, a novel combination of data sources allows for the identification of actual vehicle dimensions, rather than relying exclusively on vehicle type or vehicle weight as a proxy. The theory linking large vehicles to increased pedestrian death is largely assumed to be a result of higher front-end vehicle heights. I link precise vehicle height information to crash data for the first time to directly test this hypothesis. The results allow for counterfactual analysis that demonstrates the share of pedestrian deaths nationally that can be attributed to large vehicles, above and beyond what would occur with a

[2] A 2,000 kg object traveling at 45 mph and striking a stationary 70 kg object, where both objects are perfectly elastic, would result in the first object continuing forward at 42 mph and the second object accelerating to 87 mph. If the first object's weight was increased to 3,000 kg, the final velocities would be nearly identical at 43 mph and 88 mph. Further increasing the large object's weight results in final velocities that asymptotically approach 45 mph and 90 mph. The physics of vehicle-pedestrian collisions is far more complex. However, it remains true that when the weight ratio of two objects is very large, a marginal increase in the weight of the larger object has only a small, and asymptotically decreasing, effect on the kinetic energy transferred to the second object.

national fleet of smaller vehicles.

The paper will proceed as follows. Section 2 discusses the data sources used and how they are combined. Section 3 provides some descriptive analysis linking vehicle size to pedestrian outcomes. Section 4 outlines the regression methodology. Section 5 provides the main results. Section 6 provides a counterfactual scenario to estimate the number of pedestrians killed due to large vehicles and Section 7 concludes.

2 Data

I rely on two primary data sources to complete the analysis: (1) The National Highway Traffic Safety Administration (NHTSA) Crash Report Sampling System (CRSS) from 2016-2021, and (2) Transport Canada's Canadian Vehicle Specification (CVS) archive files.

The CRSS data is a national sample of police-reported vehicle crashes in the US, covering both fatal and non-fatal crashes. To be eligible for inclusion, the crash must include at least one motor vehicle, it must have occurred on a public roadway, and it must have led to either property damage and/or an injury or death. Data does not cover the entire US but is drawn from 60 defined geographic areas that are meant to be representative of the US as a whole, covering a diverse array of populations and geographies. Some crash types are oversampled in the data, but sampling weights are included to allow analysis to approximate a nationally representative sample of crashes. The data set contains a broad range of variables that cover characteristics of the vehicles involved in the crash, characteristics of the motorists and non-motorists involved, and details of the crash circumstances.

I filter the data to focus on incidents relevant to understanding the relationship between vehicle size and pedestrian fatality risk. I select for only crashes where exactly one vehicle and exactly one pedestrian were involved. The physical circumstances of crashes involving multiple vehicles or multiple pedestrians may be more complex. For multiple vehicle crashes, it is difficult to know with certainty in the data which vehicle struck which pedestrian. The focus on single-vehicle, single-pedestrian crashes eases the interpretation of results. I omit cyclists from the main analysis but will provide separate results specific to cyclists.

I retain characteristics of the crash, vehicle, driver, and pedestrian from the CRSS data. Crash characteristics include the estimated travel speed of the vehicle,[3] the

[3]Vehicle speed is recorded by the investigating police officer, and represents their best estimate of

local speed limit, whether alcohol was a factor in the crash, and weather and daylight conditions. I retain pedestrian and driver characteristics including age and gender. Vehicle information including vehicle type (car, light truck, compact SUV, full-size SUV, pickup, or van) is included as well as the unique VIN of the vehicle. When classifying vehicles I differentiate between compact and full-size SUVs. The current car market is dominated by SUVs, but there is significant heterogeneity in the size of vehicles within this category. I use the CRSS categories of "compact" vs "large" SUV to make this distinction.

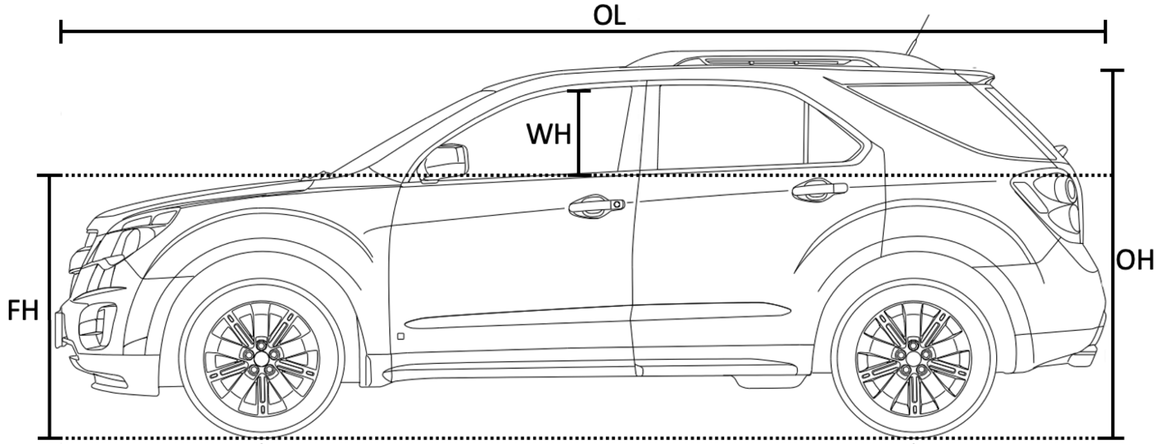
Past studies analyzing the effect of vehicle size on pedestrian outcomes have used vehicle type as a proxy for size; for example, contrasting light trucks and cars. Some past studies have also used vehicle weight information (Anderson and Auffhammer, 2014; Tyndall, 2021; White, 2004). The theory that ties vehicle size to pedestrian outcomes in transportation safety literature is largely based on the proposition that high-front-end vehicle height makes crashes more dangerous for pedestrians (Simms and Wood, 2006; Tamura et al., 2008). Front-end height is correlated with vehicle type and weight but also has significant variation that is orthogonal to these measures. A primary contribution of this paper is to test actual measurements of vehicle dimensions.

Physical vehicle dimensions are not readily available in the US in a way that could be easily merged onto federal crash data. However, Transport Canada releases an annual data set of vehicle weights and dimensions for vehicles sold in Canada for each year. Because the US and Canadian automotive markets are unified, the selection of vehicles sold in Canada is nearly identical to those sold in the US. I use Transport Canada's CVS archive files, which cover vehicle weight and physical dimensions for vehicle models sold in Canada from 1971-2022.

The CVS data records the "curb weight" for every vehicle. In addition to weight, CVS data includes many measurements of vehicle size, some of which are shown in Figure 2. The data does not explicitly include front-end height. Different designs of the front bumper and hood complicate the definition of front-end height. However, the CVS data includes a measure of the overall height of the vehicle (OH), which is measured from the ground to the highest point of the roof. Additionally, the data includes a measure of the front-side window height (WH). As represented in Figure 2, subtracting WH from OH can provide a measure for what I will refer to as front-end height (FH). The metric will be an imperfect measure of front-end vehicle height due to

how quickly the vehicle was moving based on any information the officer has from physical evidence, witness statements, or firsthand observation.

Figure 2: Canadian Vehicle Specification Measurements



OL:	Overall Length	FH:	Front Height	WH:	Window Height
		OH:	Overall Height		

The schematic diagram captures measurements recorded in the Canadian Vehicle Specification (CVS) data as well as illustrates the estimated Front Height measure. The schematic diagram was adapted from a diagram in the Transport Canada CVS 2012 User Handbook.

differences across vehicles in the distance from the top of the driver's window to the roof of the car (though this distance is small and largely standard across vehicles). I assume this distance to be five cm for all vehicles and therefore calculate front-end height as Overall Height - Window Height - 5 cm.[4] Perhaps more importantly, the measure does not account for differences in front hood slope across vehicles. However, the angle of a vehicle's hood is generally similar across consumer cars and light trucks. Therefore the proposed method of estimating front-end height should capture the large majority of true variation across vehicles.

Other vehicle dimensions captured in the CVS data will also be tested for their impact on pedestrian outcomes. Vehicle width and length (OL) in particular could be important in capturing hazards unique to larger vehicles, such as blind spots or other difficulties in safely maneuvering a large vehicle on city streets.

I merge the CRSS and CVS data sets using the following methodology. Using the VINs provided in the CRSS data, I query the NHTSA VIN decoder API to merge on

[4]While assuming a constant distance between the top of the driver's window and the roof will impact summary statistics, the assumption does not have any effect on the subsequent regression estimates. Because the approximation linearly shifts the measure of front-end height, I estimate an identical partial effect of front-end height regardless of what distance is assumed.

a list of basic vehicle make and model names as well as model years. The CVS data contains make, model, and year fields that are comparable to those generated by the VIN decoder. However, the CVS model names are more specific, providing separate information for specific subcategories of the same model.[5] I collapse down instances where there are multiple entries for the same make-model-year, taking the average value. I merge the CVS vehicle characteristics onto the CRSS data by matching vehicle make, model, and model years. The large majority of observations are matched. I manually rename some entries in the CVS data to improve matching in cases where there are clear discrepancies in naming conventions.[6]

I initially identify 13,783 crashes that involved one car and one pedestrian. 5,904 vehicles have no VIN recorded in the data. However, of observations with missing VINs 2,176 observations have make and model information manually entered in the CRSS data, which I use when VIN is not available. After dropping observations without make or model information from any source, the sample is reduced to 8,545. 308 of these observations have missing model year information. In these cases, I impute model year by using the average year among other observations in the sample of that make and model. Two instances cannot be imputed because the make and model were unique in the data.

Finally, I drop observations that do not contain a full set of covariates. Vehicle speed is a particularly important confounding variable and is often not recorded in the CRSS data. Dropping observations without estimated travel speed, or other missing covariates, reduces the final sample to 3,375.

Missing data presents an empirical challenge. While the initial CRSS sample is designed to be representative of the US, the reduced sample may be unrepresentative if the process that leads to missing data is not random. I provide summary statistics in Table 1 for the full sample of all 13,783 one-pedestrian, one-vehicle crashes, as well as the final sample of 3,375 observations for which full data is available. I find that average crash characteristics are similar across the two samples, suggesting that the

[5]For example, the CVS contains five entries that I classify as a 2010 Honda Accord (ACCORD 2DR COUPE EX-L V6, ACCORD 2DR COUPE EX/EX-L, ACCORD 4DR SEDAN EX-V6/EX-L V6, ACCORD 4DR SEDAN EX/EX-L, and ACCORD 4DR SEDAN LX). Because the vehicles in the CRSS data cannot be identified with this degree of specificity, I collapse the CVS data to a single observation for 2010 Honda Accord, which takes the average of the measurements of the six listed models.

[6]As an example of manual renaming, the CVS data contains information on "Toyota" "4Runner," while the CRSS data has entries for "Toyota" "4-Runner." I correct such spelling discrepancies to improve the match rate.

reduced sample is broadly representative of the original data set. Notably, the share of pedestrians who died is higher in the final sample. While 6.7% of crashes result in a pedestrian death in the full sample, in the restricted sample 9.1% of crashes result in a pedestrian death. It is likely the case that data collected by the police officer is completed more carefully and completely if a death occurred. I investigate the consequences of missing data in an appendix.

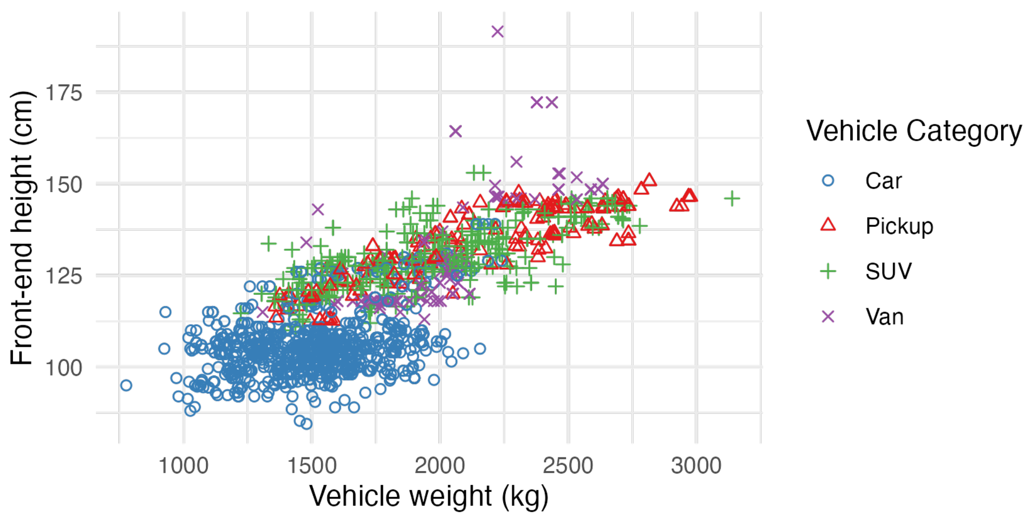
Table 1: Summary statistics

	Full Data Sample			**Final Sample**		
Variable	**Mean**	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**	**N**
Pedestrian died	0.067	0.249	13,783	0.091	0.288	3,375
Light truck	0.397	0.489	11,124	0.425	0.494	3,375
Pickup truck	0.130	0.336	11,124	0.147	0.354	3,375
Van	0.055	0.229	11,124	0.063	0.243	3,375
Compact SUV	0.164	0.370	11,124	0.156	0.362	3,375
Full-size SUV	0.048	0.213	11,124	0.060	0.237	3,375
Front-end height (meters)	1.176	0.156	8,417	1.176	0.155	3,375
Vehicle weight (100 kgs)	17.386	4.069	8,413	17.296	4.077	3,375
Travel speed (mph)	22.167	15.707	3,933	22.492	15.671	3,375
Alcohol involved	0.015	0.121	13,701	0.015	0.120	3,375
Daylight conditions	0.532	0.499	13,783	0.508	0.500	3,375
Clear weather conditions	0.730	0.444	13,783	0.726	0.446	3,375
Driver gender (female=1)	0.310	0.463	13,701	0.408	0.491	3,375
Pedestrian gender (female=1)	0.420	0.494	13,783	0.392	0.488	3,375
Driver age	43.795	17.692	10,755	43.158	18.026	3,375
Under 18 pedestrian	0.132	0.339	13,783	0.122	0.328	3,375
Over 65 pedestrian	0.171	0.376	13,783	0.231	0.421	3,375

Summary statistics are shown for the full sample of one-pedestrian one-car crashes (columns 1-3) and for the final data set for which all variables are available (columns 4-6). All variables are dummy variables except for driver age, and where units are provided.

Consumer vehicles vary widely in size. The analysis will contrast the effect of vehicle type, weight, and body dimensions. While these characteristics are correlated, the joint distributions of these size measurements are complex. Figure 3 displays the 1,810 unique vehicles (where vehicles are identified by make, model, and year) present in the final data set, showing the relationship between vehicle weight, front-end height, and body type. Front-end height and weight are generally highly correlated. The correlation coefficient is 0.78. Cars are fairly uniform in their front-end height. 94% of cars have a front-end height under 1.25 meters while only 28% of vehicles in the light truck categories have front-ends under 1.25 meters. Vehicle weight is more variable within vehicle categories, with a significant overlap in weight across the vehicle categories. The tallest vehicles are cargo vans, while "mini-vans" have front-end heights towards the bottom of the light truck distribution. The heaviest vehicle observed in the data is a 2004 Ford Excursion which weighs 3,139 kg, while the lightest vehicle is a 1989 Ford Festiva (777 kg).

Figure 3: Relationship Between Vehicle Weight, Front-end Height, and Body Type



The 1,810 unique vehicles are represented, with each point representing one unique vehicle.

Table 2 shows average vehicle size measures across vehicle types. Full-size SUVs are the heaviest class on average and are 55% heavier than the average car. Pickups are also heavy, with an average weight 51% heavier than cars. Full-size SUVs and pickups also have the highest front-end heights, 27% and 28% higher than the average car respectively. Pickups are also the longest and widest vehicles, on average.

The CRSS data spans only six years (2016-2021). However, even over this period the average size of vehicles striking pedestrians has increased. The median weight of a vehicle in a crash involving a pedestrian increased by 3% (43 kg), the median front-end height increased by 5% (6 cm), and the probability the vehicle was a light truck rather than a car increased by 11% (4.3 percentage points).

Table 2: Average Characteristics by Vehicle Type

Vehicle Type	Crashes Observed	Curb Weight (kg)	Front-end Height (cm)	Overall Height (cm)	Overall Length (cm)	Overall Width (cm)
Car	1,940	1,489	107	148	470	181
Light truck	1,435	2,055	132	182	513	194
Compact SUV	525	1,772	127	173	462	185
Full-size SUV	202	2,312	136	186	508	198
Pickup	495	2,242	137	187	564	199
Van	213	2,073	132	188	526	197

Values are averaged across all crashes observed in the final data set (N=3,375).

3 Descriptive Analysis

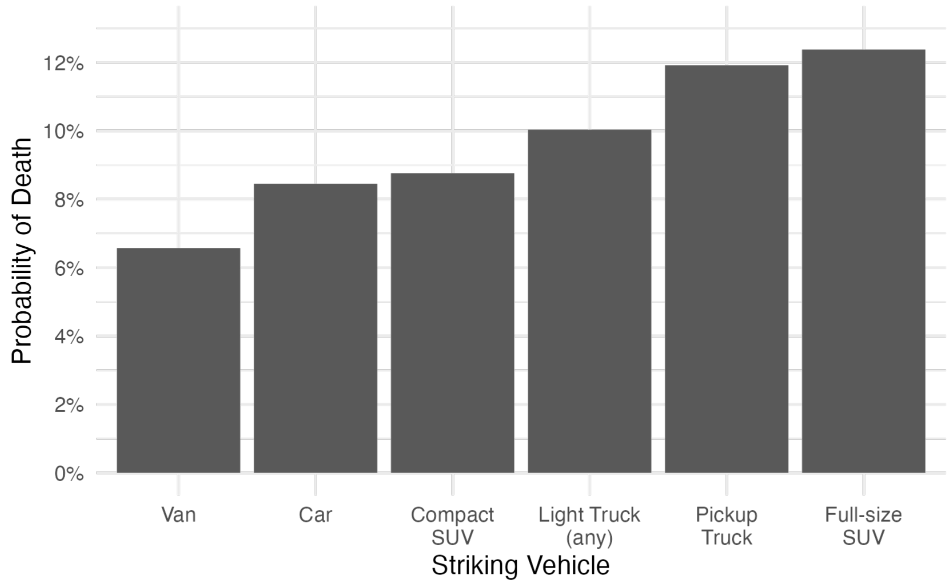
Within the final sample of 3,375 crashes, there are 308 crashes (9.1%) that resulted in the death of the pedestrian. A naive comparison of death rates across vehicle types can provide suggestive evidence of the relationship between vehicle size and pedestrian death probability. I first contrast vehicles of differing body type categories and then show correlations between pedestrian death rates and other measures of vehicle size, including front-end height.

Figure 4 shows the pedestrian death rate across crashes involving different vehicle types. There is a dramatic difference in pedestrian death probability across vehicle types. Pedestrians hit by a car die in 8.5% of crashes. For crashes involving a van, the figure is lower, at 6.6%. Compact SUV crashes have a death rate similar to cars (8.8%). Crashes involving a pickup or full-size SUV stand out as having significantly higher death rates, at 11.9% and 12.4% respectively. These correlations could be due to some vehicles being more dangerous for pedestrians, or they could be due to different vehicles being more likely to be involved in different types of crashes.

Figure 5 provides a visualization of the correlation between continuous measures of vehicle size and the probability that the pedestrian died. I use a generalized linear model (GLM) to estimate the correlation of vehicle size and the probability that the crash involved a pedestrian death. I indicate the interquartile range (IQR) in each of the graphs to provide context on the size range that vehicles typically fall into.

For curb weight, Figure 5 panel A shows that moving from the 25th to 75th per-

Figure 4: Probability a Pedestrian Dies in a Vehicle Collision



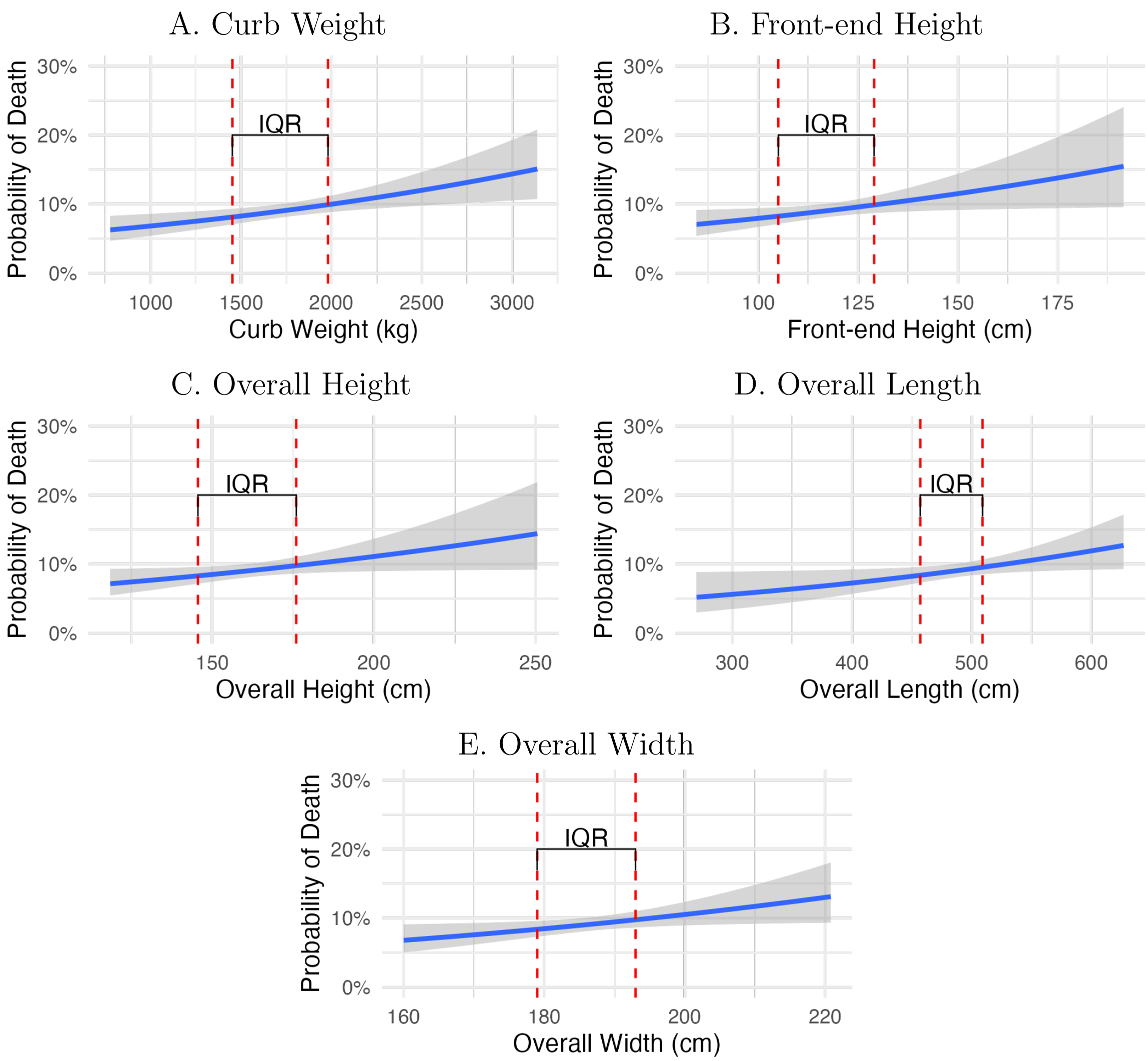
The probability a pedestrian dies after being hit by a vehicle is 9.1%. The death rate when the striking vehicle is a pickup or full-size SUV is more than 30% higher, at 11.9% and 12.4% respectively.

centile in the weight distribution results in a 23% increase in the probability a death occurred. The interquartile range of curb weight spans 1,452 to 1,981 kgs. Panel B shows the relationship for front-end height, indicating the pedestrian death rate increases by 20% when moving across the IQR. Overall height (panel C), which is highly correlated with front-end height, shows a 19% increase. The larger effect of front-end height relative to overall height suggests the front-end height measure may be more predictive of pedestrian outcomes, consistent with the mechanisms proposed in past research. The overall length and width of the vehicle also correlate with a higher death probability.

Comparing the Figure 5 panels, and the estimated effects of moving across the IQR, I find all five measures of vehicle size are consistent with larger vehicles being more dangerous for pedestrians in the event of a crash. However, the five measures are highly correlated with each other and therefore the analysis can not reveal the unique partial effect of each metric.

This section provides strictly correlative evidence. Different-sized vehicles may attract different types of drivers, they may be involved in different crash circumstances,

Figure 5: Probability a Pedestrian Dies in a Vehicle Collision



Size Measure	**Probability of Death Increase**	
	Across IQR	**Across 10th-90th Percentile**
Curb weight	23%	55%
Front-end height	20%	35%
Overall height	19%	31%
Overall length	15%	36%
Overall width	17%	36%

Generalized Linear Model lines of best fit are shown for the relationship between measures of vehicle size and the probability the involved pedestrian died. 95% confidence intervals are shown in grey.

or involve demographically different pedestrians. Controlling for these covariates in the subsequent section will better isolate the partial effect of the different measures of vehicle size.

4 Regression Methodology

Equation 1 provides the main regression equation. Each observation (i) represents one recorded crash between a vehicle and a pedestrian. D_i is a binary variable that takes a value of one if the pedestrian died as a result of the crash and 0 if the pedestrian survived. I adopt a logit regression model to accommodate the binary dependent variable. S_i is the size of the vehicle involved in the crash, I adopt several measures of vehicle size, as described. Φ is a vector of control variables that cover characteristics of the pedestrian, driver, and conditions of the crash. I include fixed effects for the year the crash occurred in (Ψ_i). The parameter of interest is β_1, which captures the partial effect of vehicle size on the probability that the pedestrian was killed.

$$D_i = \beta_0 + \beta_1 S_i + \Phi_i + \Psi_i + \varepsilon_i \tag{1}$$

CRSS is not a statistically representative sample of all crashes. The methodology used in collecting data involves oversampling some crash types.[7] I adopt the sampling weights provided in the CRSS data to make the analysis more representative of the national environment (West et al., 2008). I will also provide unweighted regression results in an appendix, and I find the weights are not important to the results.

I aim to identify the partial effect of vehicle size on the probability that a pedestrian dies, conditional on being involved in a collision. The specific conditions of a collision differ widely, and these conditions could be correlated with vehicle type. For example, the speed at which a vehicle strikes a person has been shown to be extremely important in determining the likelihood of survival (Rosen et al., 2011). An identification issue arises if vehicle speed is correlated with vehicle size. If drivers of large vehicles internalize the risk they pose to others by driving slower, the risk posed by larger vehicles could be offset by behavioral changes. Similar issues arise in any case where vehicle size is correlated with crash characteristics. By relying on microdata analysis I can introduce a vector of control variables to control for this type of endogenous mechanism to isolate the effect of vehicle size.

[7] Detailed information on the sampling methodology is provided in a Department of Transportation technical document (Zhang et al., 2019).

In the main specification, Φ includes controls for the vehicle's travel speed prior to the crash. I include both a control for speed and speed squared to capture non-linear relationships between speed and death probability. Φ also includes a control variable for the street's speed limit, and dummy variables for daylight conditions, poor weather conditions, whether the crash was in an urban environment, whether alcohol use was a reported factor in the crash, the pedestrian's gender, the driver's gender, whether the pedestrian was under 18 years of age, and whether the pedestrian was over 65 years of age.

Some past studies have noted the importance of driver or crash characteristics being correlated with vehicle choice (Gayer, 2004; Toy and Hammitt, 2003). For example, large pickups and SUVs are marketed to consumers based on their "toughness" and "ruggedness." Consumers who respond to this marketing could also share particular driving behaviors. I can control for this effect to the extent it is captured by driver age, gender, or observable characteristics of the crash.

The gender of the driver may be an important confounding variable. In the full CRSS sample, I identify 1,423 single-vehicle, single-pedestrian crashes that involve a pickup truck. Of these crashes, 89% (1,271 crashes) involve a male driver. For full-size SUVs, males are driving only 56% of the time. Across all vehicle types, men are the driver in 69% of crashes. The enormous discrepancy in gender representation for pickup-pedestrian crashes suggests strongly divergent vehicle preferences by gender. In correlative evidence (for example Figure 4), differences in pedestrian outcomes across vehicle types could also be attributed to differing driver behaviours across genders. In the subsequent regression analysis, I control for driver gender, and further analyze the role of gender.

The data set omits crashes where no police records of the crash were generated. If vehicle size is correlated with the probability of a police report being generated among non-fatal crashes, results could be biased. For example, perhaps large vehicles are more likely to cause property damage in non-fatal crashes, and therefore police reports are more common in crashes where a large vehicle is involved. As discussed in Anderson and Auffhammer (2014), if vehicle size is positively correlated with the probability of a crash generating a police report in a non-fatal crash, then the estimated effect of vehicle size on pedestrian deaths represents a lower bound of the true effect. When studying motorist safety, Anderson and Auffhammer (2014) suggested that larger vehicles could be less likely to generate a police report in their setting because large vehicles may be less likely to sustain damage to the vehicle itself. In the case of pedestrian incidents, damage to the vehicle is not a primary factor in generating a police report. The severity of the pedestrian injury is what dictates police involvement, therefore the estimates are more clearly lower bounds of the true effect. If large vehicles are more dangerous for pedestrians, they may generate additional police-reported crashes because the same crash involving a small vehicle might result in less severe pedestrian injuries that do not generate a police report. Therefore, the results presented will understate the safety risk of large vehicles to the extent large vehicles generate more non-fatal police reports than small vehicles, conditional on crash characteristics.

5 Results

Results from the Equation 1, logit regression are shown in Table 3. I first show results based on vehicle body type in columns 1-2. In both regressions the omitted group is passenger car, allowing coefficients to be interpreted as the effect of the body type relative to a car. Column 1 shows the impact of the vehicle being any type of light truck. I find the chance of the pedestrian dying is 68% higher when being hit by a light truck relative to a car, holding constant vehicle speed, and other characteristics of the crash. The result provides strong evidence that light trucks are more dangerous for pedestrians in the event of a collision, consistent with past studies.

Table 3, column 2 breaks out the light truck variable into its constituent categories, estimating the partial effect of a vehicle class on the probability of pedestrian death. I find compact SUVs, full-size SUVs, and pickup trucks all result in a significantly higher probability of pedestrian death when compared to a similar collision involving a car. Compact SUVs increase the probability of death by 63%, pickups increase the probability by 68%, and full-size SUVs increase the probability by 99%. The results of vehicle type on pedestrian death risk from Table 1 are illustrated in Figure 6. I do not find a statistically significant difference in pedestrian death probability between cars and vans; however, the coefficient estimate on vans suggests they are 41% more likely to result in a death. While vans had a lower death rate than cars in the raw data, controlling for crash characteristics isolates a positive but insignificant effect of vans. The pattern suggests vans are over-represented among minor crashes.

The estimates suggest full-size SUVs and pickup trucks pose the greatest danger to pedestrians in a collision, consistent with prior research that has argued high-front-end designed vehicles elevate pedestrian risk. Full-size SUVs and pickups have the highest average front-end heights within the data set (Table 2). The result that pickup trucks

Table 3: Effect of Vehicle and Crash Characteristics on Pedestrian Death Probability

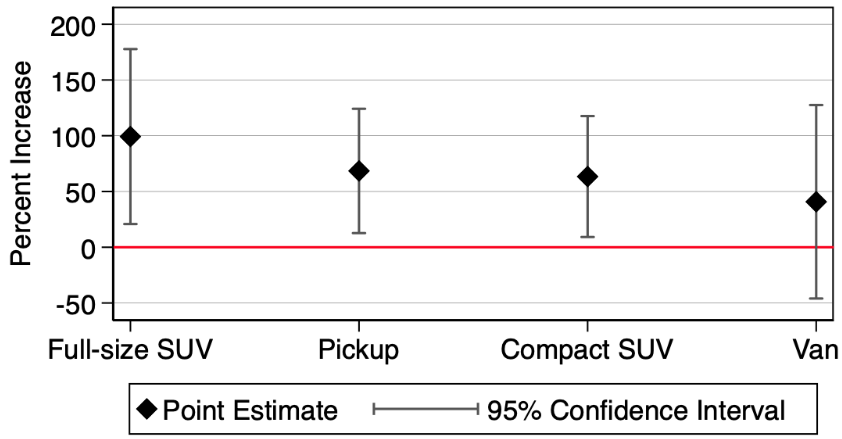
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Light truck	0.517**						
	(0.153)						
Compact SUV		0.491*		0.350		-0.033	-0.018
		(0.221)		(0.227)		(0.286)	(0.292)
Full-size SUV		0.689*		0.274		-0.074	-0.115
		(0.295)		(0.373)		(0.408)	(0.416)
Pickup truck		0.521*		0.135		-0.237	-0.271
		(0.226)		(0.295)		(0.337)	(0.343)
Van		0.342		0.037		-0.386	-0.398
		(0.319)		(0.367)		(0.444)	(0.444)
Vehicle weight (100 kgs)			0.064**	0.051			0.015
			(0.019)	(0.029)			(0.036)
Front end height (meters)					2.007**	2.477**	2.209*
					(0.475)	(0.886)	(1.118)
Travel speed (mph)	0.102**	0.102**	0.103**	0.103**	0.102**	0.103**	0.103**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Travel speed squared (mph)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Posted speed limit (mph)	0.032**	0.032**	0.031**	0.032**	0.031**	0.031**	0.031**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Alcohol involved	0.060	0.067	0.069	0.068	0.071	0.068	0.068
	(0.222)	(0.220)	(0.223)	(0.220)	(0.221)	(0.218)	(0.218)
Daylight conditions	-1.097**	-1.087**	-1.097**	-1.089**	-1.110**	-1.100**	-1.099**
	(0.193)	(0.195)	(0.195)	(0.196)	(0.195)	(0.197)	(0.197)
Clear weather conditions	-0.004	-0.012	0.000	-0.010	0.001	-0.012	-0.011
	(0.179)	(0.177)	(0.182)	(0.178)	(0.180)	(0.176)	(0.177)
Urban environment	-0.116	-0.097	-0.132	-0.114	-0.127	-0.121	-0.123
	(0.223)	(0.226)	(0.223)	(0.226)	(0.225)	(0.228)	(0.228)
Driver gender (female=1)	0.014	0.012	0.037	0.024	0.040	0.006	0.010
	(0.158)	(0.160)	(0.157)	(0.159)	(0.159)	(0.160)	(0.159)
Pedestrian gender (female=1)	0.522**	0.529**	0.539**	0.534**	0.547**	0.549**	0.549**
	(0.156)	(0.156)	(0.156)	(0.156)	(0.156)	(0.156)	(0.157)
Driver age	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Under 18 pedestrian	-1.056**	-1.057**	-1.037**	-1.067**	-1.074**	-1.099**	-1.097**
	(0.372)	(0.367)	(0.371)	(0.367)	(0.371)	(0.367)	(0.366)
Over 65 pedestrian	0.844**	0.837**	0.867**	0.849**	0.848**	0.837**	0.841**
	(0.170)	(0.171)	(0.170)	(0.171)	(0.171)	(0.172)	(0.172)
Crash year fixed effects	Y	Y	Y	Y	Y	Y	Y
N	3375	3375	3375	3375	3375	3375	3375

Significance levels: $*$: 5% $**$: 1%. Robust standard errors are shown in parenthesis. Regressions are estimated with sampling probability weights.

pose a particular danger to pedestrians is consistent with the recent findings in Edwards and Leonard (2022). The differences in estimates for compact and full-size SUVs suggest that size variation within the SUV class plays an important role in pedestrian safety.

Table 3, columns 3-7 provide results that make use of the physical vehicle measurements from the Transport Canada database. Column 3 tests for the effect of vehicle

Figure 6: Change in Probability of Pedestrian Death Relative to Car



Results of Table 1 regressions are shown for comparison. Full-size SUVs are shown to increase the risk of a pedestrian death by 99%, conditional on collision characteristics.

weight, including the standard control variables for crash circumstances. I find a highly significant relationship between vehicle weight and pedestrian death risk. A 100 kg increase in vehicle weight relates to a 6.6% increase in the probability the pedestrian dies. The interquartile range of weight is 1,452 kg to 1,981 kg. Moving from the 25th to 75th percentile in vehicle weight increases pedestrian death risk by 35%.

In column 4 I add controls for vehicle body type. Vehicle weight and body type are correlated. Including body type controls reduces the estimated effect of weight by 20%, and the effect is no longer significant at the 5% level.

Columns 5 and 6 use front-end vehicle height as the measure of vehicle size. I find that a 10 cm increase in front-end height relates to a 22% increase in pedestrian death probability (column 5). The interquartile range of vehicle heights in the data set is 1.05 meters to 1.29 meters. Moving across the interquartile range causes a 53% increase in the probability the pedestrian dies. The result provides clear evidence that tall front-end vehicle designs raise pedestrian death probability substantially.

The large effect of front-end height across the interquartile range, relative to vehicle weight, suggests that front-end design may be a more important factor than overall weight. In column 4 I include vehicle body type controls. Controlling for vehicle body type actually increases the partial effect of front-end vehicle height, suggesting high-front-end designs are specifically culpable for higher pedestrian death rates, and this is not driven by other characteristics that are correlated with front-end height. After controlling for body type, I estimate a 10 cm increase in front-end height translates to a 28% increase in pedestrian death.

In column 7, I include vehicle weight, front-end height, and body type controls in the same regression. The only vehicle size measure that remains statistically significant is front-end height, which maintains its magnitude. The strong predictive strength of front-end height relative to the other size measures provides more evidence of its importance in pedestrian safety.

Several control variables are a strong predictor of pedestrian outcome. Conditional on vehicle type and other characteristics, increasing a vehicle's speed from 30 mph to 40 mph raises the probability of pedestrian death by 111%. Increasing speed from 30 to 50 mph raises the probability of death by 312%. Vehicle speed dramatically increases the probability the pedestrian dies. Within the final data sample, crashes where the speed was below 30 mph only resulted in a pedestrian death in 2.0% of crashes, whereas crashes exceeding 30 mph resulted in death in 25.4% of crashes.

Daylight conditions are also an important predictor of pedestrian survival. In the final sample of data, the pedestrian death rate during daylight hours is 2.8%, while at night the death rate is 15.6%. Within the regression framework, conditional on other crash characteristics, the probability of pedestrian death is three times higher if the crash occurred at night.

While the gender of the driver does not significantly impact the probability of pedestrian survival, the pedestrian's gender is important. In the raw data, death rates are similar for men and women; 9.4% for male pedestrians and 8.7% for female pedestrians. However, holding constant the characteristics of the crash, women are much more likely to die. Under similar crash conditions, female pedestrians die at a rate 70% higher than men (Table 3). The difference between the raw data and the regression result suggests that women are involved in very different types of crashes. For example, the average vehicle speed for crashes with a female pedestrian is lower. Female-pedestrian crashes have an average vehicle speed of 19.2 mph, while for male pedestrian crashes the mean is 24.6 mph.

The high probability of female pedestrian death could also relate to the interaction between average female body height and the effect of vehicle front-end height. Similarly, children might be more affected by high-front-end designs because of their shorter bodies. Table 4 provides split-sample results comparing crashes with male vs female pedestrians (columns 1 and 2) as well as comparing adult vs child pedestrians (columns 3 and 4). The regression approach mirrors Table 3, column 5. I find that the partial effect of vehicle front-end height is much larger for women and children. While a 10 cm increase in front-end height raises male pedestrian death probability by 19%, it raises female pedestrian death probability by 31%. A 10 cm increase raises the death probability of 18-65 year old pedestrians by 21%, while it raises the probability a child pedestrian will die by 81%, roughly four times the effect among adults.

Table 4: Effect of Vehicle and Crash Characteristics on Pedestrian Death Probability: Split Sample Results

	(1)	(2)	(3)	(4)
Front end height (meters)	1.749**	2.707**	1.887**	5.925**
	(0.613)	(0.766)	(0.483)	(2.067)
Travel speed (mph)	0.110**	0.073*	0.104**	-0.100*
	(0.026)	(0.030)	(0.019)	(0.050)
Travel speed squared (mph)	-0.001	0.000	-0.000	0.003
	(0.000)	(0.000)	(0.000)	(0.001)
Posted speed limit (mph)	0.025	0.041*	0.030**	0.127*
	(0.013)	(0.017)	(0.011)	(0.057)
Alcohol involved	-0.056	0.455	0.054	0.000
	(0.239)	(0.536)	(0.220)	(.)
Daylight conditions	-1.076**	-1.280**	-1.121**	-1.833
	(0.246)	(0.318)	(0.201)	(1.399)
Clear weather conditions	-0.094	0.169	0.006	-0.373
	(0.220)	(0.292)	(0.184)	(1.277)
Urban environment	-0.256	0.307	-0.087	-1.469
	(0.279)	(0.381)	(0.229)	(0.983)
Driver gender (female=1)	0.082	-0.007	0.043	0.067
	(0.199)	(0.273)	(0.162)	(0.654)
Pedestrian gender (female=1)			0.492**	2.132
			(0.159)	(1.217)
Driver age	-0.002	0.000	-0.002	0.011
	(0.006)	(0.007)	(0.005)	(0.020)
Under 18 pedestrian	-2.072**	-0.314		
	(0.732)	(0.472)		
Over 65 pedestrian	0.681**	1.223**	0.845**	0.000
	(0.216)	(0.294)	(0.170)	(.)
Crash year fixed effects	Y	Y	Y	Y
Pedestrian subsamble	Male Pedestrians	Female Pedestrians	Adult Pedestrains	Child Pedestrians
N	2053	1322	2962	411

Significance levels: $*$: 5% $**$: 1%. Robust standard errors are shown in parenthesis. Regressions are estimated with sampling probability weights.

Table 4 Column 3 estimates a unique effect for those over 65, showing a 10 cm increase in front-end height raises the probability a pedestrian over 65 will die by 31%. The higher rate for older pedestrians suggests they are also more vulnerable to high-front-end vehicles.

The inclusion of crash-level control variables across regression specifications helps to isolate the effect of vehicle size by removing the effect of crash-specific characteristics that may be important to determining pedestrian survival in a particular crash. However, it is possible that drivers with particular characteristics select particular vehicle types and that drivers of larger vehicles endogenously change their behavior to internalize the risks of driving a larger vehicle. In fact, light trucks do tend to hit pedestrians at lower speeds compared to cars within the sample. For pedestrian crashes involving a car, the average collision speed was 23.5 mph, while the average speed in crashes involving a light truck was 21.1 mph. Drivers of larger vehicles might be internalizing their external risks by driving more slowly. I reestimate the main results while omitting the vehicle speed control variable (Appendix A). These regressions might better capture the overall danger presented by large vehicles by allowing driver's speed to be an endogenous characteristic of vehicle type. I find the effect of vehicle size falls by about 15% when collision speed is not controlled for. While drivers of larger vehicles appear to internalize a portion of the risk by driving more slowly, this accounts for only a fraction of the additional danger caused by the large body size in a collision.

In Appendix B, I provide a comprehensive sensitivity analysis where I provide results across all possible combinations of crash-level control variables. I find results are robust across the large majority of possible specifications. In Appendix C I provide alternative results where I do not use the CRSS-provided crash sample weights. I also find results are robust to not using sample weights.

I focus analysis on pedestrian outcomes. Cyclists may confront similar dynamics as larger vehicles may present similar dangers.[8] Using a method analogous to my pedestrian analysis, I observe 3,239 instances of one-vehicle one-cyclist crashes, creating a similar sample size to the pedestrian data set. However, cyclist survival rates are much higher. While I observe 308 pedestrian deaths, I observe only 61 cyclist deaths. The limited number of deaths observed reduces the statistical power when testing for effects on cyclist survival. Nevertheless, I report cyclist results in Appendix D. I find that a cyclist hit by a light truck is 99% more likely to die than when hit by a car. I find pickup trucks have the largest effect, with cyclists 291% more likely to die when struck by a pickup rather than a car. I find a 100 kg increase in vehicle weight increases the cyclist death rate by 7.4%. A 10 cm increase in front-end height relates to a 25.5%

[8]A report by the Insurance Institute for Highway Safety (IIHS) examining 71 vehicle-cyclist crashes concluded that crashes involving an SUV were more likely to result in serious injury than those involving cars (Monfort and Mueller, 2023). The report argued that results were likely driven by the higher front-end design of SUVs relative to cars.

increase in cyclist death probability, though this effect is not statistically significant. The estimates suggest that light trucks are also perilous for cyclists, but the limited variation in the data means that the results should be interpreted with caution.[9]

6 Counterfactual Analysis

Regression results provide evidence that larger vehicle sizes increase the likelihood a pedestrian dies in a collision. Applying the above estimates to national road fatality data can provide a sense of the overall magnitude of the pedestrian safety costs posed by larger vehicles. In this section, I provide an estimate of how many pedestrian deaths can be attributed to the presence of large vehicles. I first consider the vehicle body type estimates and then consider front-end height effects.

In 2021, 7,388 pedestrians were killed. Of these deaths, I estimate 5,846 were struck by passenger vehicles (rather than commercial trucks, buses, or other vehicle categories).[10] Compact SUVs accounted for 17.6% of these passenger vehicles. Therefore, about 1,026 people are killed annually from being struck by a compact SUV. As estimated above, conditional on crash characteristics, being struck by a compact SUV rather than a car increases the probability of pedestrian death by 63% (Table 3, column 2). The estimate implies that, among the 1,026 pedestrians who were killed by compact SUVs, only 628 would have died if that cohort had been struck by a car rather than a compact SUV. Therefore, in a counterfactual environment where all compact SUVs were replaced with cars, about 398 fewer pedestrians would be killed each year.

I perform similar calculations for the other subcategories of light trucks and provide estimates in Table 5. I estimate that if all light trucks were replaced with cars in 2021, 1,179 fewer pedestrians would have died. Among these deaths, pickups comprise the largest share, responsible for 459 annual deaths. While full-size SUVs were found to be the most dangerous, they are also relatively uncommon compared to other vehicle types. Compact SUVs contribute the second-highest number of induced deaths (398). While compact SUVs are less dangerous than pickups or full-size SUVs, they are very common and therefore contribute significantly to pedestrian deaths. I estimate that full-size SUVs induce 227 annual pedestrian deaths and Vans induce 95, relative to a

[9]For example, the estimated effect of full-size SUVs is negative (though insignificant). I observe only two instances in the data of a cyclist fatality involving a full-size SUV.

[10]I use the full 2021 FARS data set. Among the 7,388 pedestrian deaths, I can identify the striking vehicle in 6,308 of the crashes by examining one-vehicle, one-person crashes. I estimate the share of deaths coming from each vehicle type based on this subsample of observations.

scenario where these vehicle types were replaced with cars.

Table 5: Counterfactual Estimates of Pedestrian Lives Saved if Vehicle Categories were Replaced with Cars

	Exogenous Speed Assumed		Speed Differential	Endogenous Speed Assumed	
	Total	**%**		**Total**	**%**
Compact SUVs	398	5.4%	-2.48 mph	235	3.2%
Full-size SUVs	227	3.1%	-2.03 mph	179	2.4%
Pickup trucks	459	6.2%	-2.18 mph	308	4.2%
Vans	95	1.3%	-2.79 mph	26	0.4%
All light trucks	1,179	16.0%		749	10.1%

Excess deaths indicate the number of annual pedestrian deaths that would have been avoided if that class of vehicle were replaced with cars. The "%" columns show the share that these deaths represent of the 7,388 annual pedestrian deaths that occurred in the final year of the study period.

Relative to the annual pedestrian death count (7,388), the counterfactual estimates suggest that the presence of light trucks can account for 16% of annual pedestrian deaths. The result suggests pedestrian mortality could be meaningfully lowered by shifting towards smaller vehicles.

Tyndall (2021) estimated that if all light trucks on US roads were replaced with cars, 459 pedestrian deaths would have been averted in 2019. Using 2019 pedestrian fatality data, the estimates of the current paper imply converting all light trucks to cars would have averted 1,001 pedestrian deaths in 2019. The estimate from Tyndall (2021) excluded rural areas, which comprised 14% of the US population. Therefore, the two studies reach broadly consistent conclusions despite using substantially different methodologies, with the current study finding a somewhat larger effect.

Front-end height was found to be the strongest predictor of pedestrian death of the size measures studied (Table 3). For counterfactual analysis, I consider a hypothetical regulation that caps the front-end height of vehicles to be no more than 1.25 meters. This threshold would require design changes for large, popular pickups such as Ford F-series trucks or the Chevrolet Silverado, but would not require design changes for many compact SUVs. For example, the Honda CR-V, a popular compact SUV, has a front-end height of 1.25 meters. In the final sample analyzed in this study, 40% of vehicles involved in a fatal pedestrian crash had a front-end height above 1.25 meters. The figure implies that across 5,846 annual pedestrian deaths from passenger vehicles, 2,315 involved a vehicle with a front-end height above 1.25 meters. I take the front-end heights of all vehicles that struck and killed a pedestrians in the final CRSS sample. I then calculate by how much each exceeded the 1.25 meter limit. Complying with the 1.25 meter limit would require the average non-conforming vehicle to reduce its front-end height by 12 cm. Using Table 3, column 3 results, I can estimate the reduction in pedestrian death likelihood that would have occurred had each fatal crash involving a vehicle with a front-end above 1.25 meters instead had a 1.25 meter front-end. I estimate the policy would improve the chance of survival for pedestrians struck by these non-conforming vehicles by an average of 24.0%. Across the 2,315 pedestrians killed by high-front-ended vehicles (>1.25 m), I estimate 555 lives would be saved annually by adopting a 1.25 meter front-end limit. The lives saved equal 8% of annual pedestrian deaths. Reducing the limit to 1.2 meters would spare an estimated 812 pedestrian lives per year, and further reducing the cap to 1.1 meters would spare an estimated 1,415 pedestrian lives per year.

The above counterfactual results apply to a scenario where drivers change vehicles but do not endogenously alter their driving behavior. As discussed, drivers of larger vehicles may internalize the danger they pose to pedestrians, or other road users, by driving more slowly. When a collision involves a light truck rather than a car, the reported speed of the vehicle is lower. In Table 5 I report the average speed differential of each vehicle type relative to crashes involving a car. Light trucks have average crash speeds of 2.0-2.8 mph lower than cars. Full-size SUVs crash only 2.0 mph slower, on average, while vans crash 2.8 mph slower, on average.

Table 3 results provided consistent estimates of the partial effect of vehicle speed (and vehicle speed squared) on the probability the pedestrian died. I use these estimates to subtract out the partial effect of the endogenous change in vehicle speed observed for each light truck type. I then recalculate the implied excess pedestrian deaths for each vehicle type. This second counterfactual environment applies to a scenario where light truck drivers switch to cars, but also drive faster, consistent with the observed average differential in crash speed. The results are reported in Table 5. Accounting for endogenous speed reduces the estimated benefits, as the improvement in pedestrian safety from the reduced vehicle size is partially offset by the higher impact speed. The alternative results imply that light trucks are responsible for 749 deaths per year, relative to a world where these vehicles are replaced with cars. Accounting for endogenous speed reduces the estimated number of deaths avoided by 36%. The alternative results also suggest the impact of the hypothetical 1.25 meter front-end cap would reduce annual pedestrian deaths by only 387, rather than the 555 estimated when speed was assumed exogenous.

It is not obvious that switching to a different vehicle would alter the driver's speed in collisions. Vehicle speed might be a symptom of driver characteristics and persist regardless of vehicle. Drivers who tend to drive quickly might be endogenously selecting cars, rather than light trucks. If driving speed is a characteristic of the driver, then the exogenous vehicle speed counterfactual estimates will be most applicable. If vehicle speed is determined more by the vehicle type, then the endogenous vehicle speed counterfactual estimates would be most applicable. If both conditions are relevant, the two counterfactual estimates may reasonably provide a bound of the true effect, which suggests light trucks cause between 749-1,179 excess pedestrian deaths relative to a scenario where all light trucks were replaced with cars. Similarly, front-end heights that exceed 1.25 meters cause between 387 and 555 annual pedestrian deaths. In either case, I find a significant share (10-16%) of pedestrian deaths are the result of light trucks in general, with 5-8% of annual deaths specifically caused by front-end heights that exceed 1.25 meters.

7 Conclusion

The average size of US vehicles has grown significantly over recent years. At the same time, the number of pedestrians dying in crashes each year has risen significantly. I combine data on pedestrian crashes and vehicle size measurements in a novel way to directly test for the impact of vehicle size on the probability a pedestrian dies in a crash. I find that full-size SUVs and pickup trucks pose a particular danger for pedestrians. A pedestrian hit by a full-size SUV is twice as likely to die than a pedestrian hit by a car under similar circumstances, while being hit by a pickup truck rather than a car increases the death probability by 68%. I find that high-front-end vehicle designs are particularly culpable for the higher pedestrian death rate attributable to large vehicles. A 10 cm increase in the front-end height of a vehicle increases the risk of pedestrian death by 22%. Conditional on multiple measures of vehicle size, front-end height displays the most statistically significant effect.

Of the 7,388 pedestrians who died in 2021, I estimate that roughly 1,000 were killed because of the increased risks posed by large vehicle types. While full-size SUVs pose the greatest safety risk for pedestrians in a crash, pickups and compact SUVs are more common on US roads, and therefore contribute to more deaths overall.

The shift towards electric vehicles is projected to make vehicles heavier still, as the batteries needed to power the vehicles add significant weight (Shaffer et al., 2021). If a strong relationship between pedestrian fatalities and vehicle weight exists, the number of fatalities attributable to vehicle size will likely continue to rise in the coming years. However, I find that once front-end height is controlled for, the impact of vehicle weight is relatively small, suggesting the regulation of body design may be more important for pedestrian safety than the regulation of vehicle weight per se. However, because the two measures are highly correlated in practice, weight regulations could generate positive pedestrian safety effects.

The burden of pedestrian deaths is not shared equally. I find that women, children, and the elderly experience the largest deterioration in safety from larger vehicles. Other research has shown that racial minorities carry a larger burden of pedestrian crash risk. Nehiba and Tyndall (2022) examined pedestrian deaths on US interstate highways, finding Black pedestrians are significantly more likely to be victims. Roll and McNeil (2022) examined pedestrian fatalities in Oregon, also finding that poor and minority residents are more likely to be the victims. Nationally, Sanders and Schneider (2022) provided a detailed accounting of the large racial disparities in pedestrian death risk. Because of greater exposure to high-risk vehicle traffic, low-income and minority populations will likely comprise a disproportionate share of the increased deaths attributable to growing vehicle sizes.

While 40% of vehicles included in this study's crash data were light trucks, 78% of vehicles sold or leased in the US in 2021 fall into this category. Within vehicle categories, the average size of vehicles has also been increasing. As vehicles age out of the fleet, the vehicles that replace them will tend to be larger. Therefore, the average size of vehicles on US roads will continue to increase in the short term. As shown, larger vehicles have a clear relationship to pedestrian mortality, suggesting larger vehicle sizes are likely to push pedestrian fatality rates up higher than they would otherwise be barring regulatory changes to vehicle design standards.

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Appendix A: Sample Representativeness and Missing Observations

The main analysis of this paper is executed on a subsample of data for which a full set of variables are available. While I study 3,375 crashes in the main analysis, I observe over 13,000 one-vehicle one-pedestrian crashes in the full data set. Vehicle speed is an important control variable but is missing for many crashes in the CRSS data. I observe over 7,000 one-vehicle one-pedestrian crashes where all variables except speed are recorded. In this appendix, I examine the effect of missing data.

In Table A1 I present results using the sample used in the main analysis (N=3,375), but omitting speed as a control. I find that omitting speed as a control lowers the estimated effect of vehicle size by roughly 15-20%, depending on the measure of size used. The result is consistent with the results provided in Section 6, wherein larger vehicles tend to crash at lower speeds. The endogenous speed effect only offsets a fraction of the increased risk posed by large vehicles.

In Table A2, I complete the same analysis as in Table A1 but include all available crash data, including those where crash speed was not recorded. I find the estimated effect of vehicle size on pedestrian survival is very similar when using the expanded sample. For example, moving to the full sample increases the estimated effect of switching from a car to a light truck by 7% (Tables A1 and A2, column 1), but decreases the estimated effect of front-end height by 7% (Tables A1 and A2, column 5). These results provide some evidence that the restricted sample is generally representative of the dynamics that appear in the full sample.

Table A1: Effect of Vehicle and Crash Characteristics on Pedestrian Death Probability, No Crash Speed Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Light truck	0.438**						
	(0.145)						
Compact SUV		0.410*		0.285		-0.009	0.005
		(0.206)		(0.215)		(0.267)	(0.272)
Full-size SUV		0.604*		0.253		0.009	-0.036
		(0.282)		(0.351)		(0.382)	(0.391)
Pickup truck		0.412*		0.073		-0.196	-0.235
		(0.209)		(0.285)		(0.321)	(0.331)
Van		0.368		0.113		-0.185	-0.200
		(0.316)		(0.355)		(0.413)	(0.413)
Vehicle weight (100 kgs)			0.054**	0.044			0.017
			(0.018)	(0.028)			(0.034)
Front end height (meters)					1.680**	1.977*	1.688
					(0.453)	(0.838)	(1.037)
Posted speed limit (mph)	0.097**	0.097**	0.096**	0.097**	0.097**	0.097**	0.097**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Alcohol involved	0.170	0.168	0.179	0.172	0.181	0.173	0.174
	(0.220)	(0.219)	(0.220)	(0.218)	(0.219)	(0.217)	(0.217)
Daylight conditions	-1.480**	-1.475**	-1.480**	-1.480**	-1.496**	-1.492**	-1.491**
	(0.179)	(0.180)	(0.181)	(0.182)	(0.180)	(0.182)	(0.182)
Clear weather conditions	0.047	0.040	0.045	0.036	0.051	0.037	0.036
	(0.166)	(0.165)	(0.168)	(0.166)	(0.167)	(0.165)	(0.165)
Urban environment	-0.262	-0.245	-0.272	-0.259	-0.269	-0.265	-0.267
	(0.209)	(0.213)	(0.210)	(0.212)	(0.210)	(0.213)	(0.213)
Driver gender (female=1)	-0.139	-0.143	-0.116	-0.131	-0.116	-0.142	-0.138
	(0.150)	(0.153)	(0.151)	(0.153)	(0.152)	(0.152)	(0.152)
Pedestrian gender (female=1)	0.337*	0.338*	0.345*	0.342*	0.352*	0.351*	0.350*
	(0.149)	(0.149)	(0.149)	(0.149)	(0.149)	(0.149)	(0.149)
Driver age	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Under 18 pedestrian	-0.884*	-0.891*	-0.862*	-0.886*	-0.885*	-0.905*	-0.901*
	(0.382)	(0.379)	(0.381)	(0.376)	(0.379)	(0.374)	(0.374)
Over 65 pedestrian	0.826**	0.821**	0.841**	0.830**	0.824**	0.817**	0.821**
	(0.162)	(0.162)	(0.162)	(0.162)	(0.162)	(0.162)	(0.162)
Crash year fixed effects	Y	Y	Y	Y	Y	Y	Y
N	3375	3375	3375	3375	3375	3375	3375

Significance levels: $*$: 5% $**$: 1%. Robust standard errors are shown in parenthesis. Regressions are estimated with sampling probability weights.

Table A2: Effect of Vehicle and Crash Characteristics on Pedestrian Death Probability, No Crash Speed Controls and Expanded Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Light truck	0.468**						
	(0.110)						
Compact SUV		0.489**		0.461**		0.228	0.203
		(0.153)		(0.165)		(0.199)	(0.198)
Full-size SUV		0.394		0.359		0.030	0.085
		(0.219)		(0.278)		(0.282)	(0.293)
Pickup truck		0.525**		0.440		0.158	0.160
		(0.159)		(0.236)		(0.264)	(0.268)
Van		0.290		0.204		-0.036	-0.072
		(0.243)		(0.290)		(0.304)	(0.315)
Vehicle weight (100 kgs)			0.039**	0.007			-0.021
			(0.013)	(0.021)			(0.026)
Front end height (meters)					1.561**	1.233*	1.645*
					(0.322)	(0.616)	(0.730)
Posted speed limit (mph)	0.088**	0.088**	0.089**	0.090**	0.088**	0.088**	0.090**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Alcohol involved	0.224	0.228	0.260	0.259	0.248	0.248	0.260
	(0.144)	(0.144)	(0.145)	(0.146)	(0.145)	(0.145)	(0.146)
Daylight conditions	-1.468**	-1.469**	-1.441**	-1.454**	-1.474**	-1.477**	-1.462**
	(0.136)	(0.137)	(0.137)	(0.137)	(0.137)	(0.137)	(0.137)
Clear weather conditions	0.054	0.057	0.035	0.046	0.056	0.060	0.052
	(0.124)	(0.124)	(0.125)	(0.125)	(0.125)	(0.124)	(0.124)
Urban environment	-0.510**	-0.505**	-0.486**	-0.479**	-0.507**	-0.507**	-0.481**
	(0.129)	(0.130)	(0.129)	(0.131)	(0.130)	(0.132)	(0.132)
Driver gender (female=1)	-0.040	-0.032	-0.022	-0.020	-0.029	-0.032	-0.032
	(0.113)	(0.114)	(0.113)	(0.115)	(0.114)	(0.115)	(0.115)
Pedestrian gender (female=1)	0.117	0.115	0.120	0.120	0.111	0.107	0.122
	(0.115)	(0.115)	(0.116)	(0.117)	(0.116)	(0.117)	(0.117)
Driver age	-0.010**	-0.010**	-0.009**	-0.010**	-0.009**	-0.009**	-0.009**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Under 18 pedestrian	-0.537*	-0.535*	-0.479	-0.493	-0.516*	-0.516*	-0.510
	(0.261)	(0.261)	(0.262)	(0.262)	(0.261)	(0.261)	(0.260)
Over 65 pedestrian	0.777**	0.775**	0.806**	0.797**	0.796**	0.795**	0.800**
	(0.127)	(0.127)	(0.127)	(0.128)	(0.127)	(0.127)	(0.128)
Crash year fixed effects	Y	Y	Y	Y	Y	Y	Y
N	7241	7241	7137	7137	7140	7140	7131

Significance levels: $*$: 5% $**$: 1%. Robust standard errors are shown in parenthesis. Regressions are estimated with sampling probability weights.

Appendix B: Robustness to Alternative Sets of Control Variables

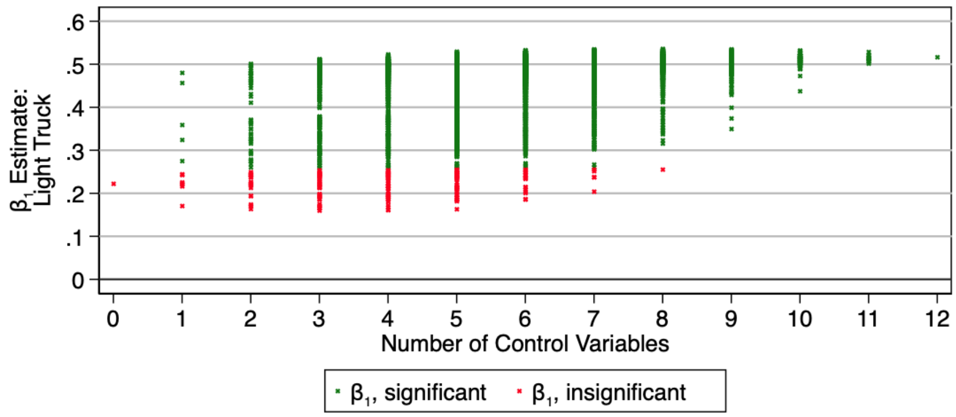
The main regression specification in this paper included 12 control variables, capturing crash characteristics. In this appendix, I show the robustness of the paper's main findings to using different subsets of these 12 covariates. I run regressions for every possible combination of the 12 controls, ranging from no controls to all 12. Figure B1 shows the estimated effects on pedestrian death of the vehicle being a light truck rather than a car (B1.i), the estimated effect of a one-meter increase in front-end height (B1.ii), and the estimated effect of a 100 kg increase in curb weight (B1.iii). The leftmost points in each scatter represent the β_1 estimates when none of the 12 covariates are included. The rightmost points indicate the β_1 estimate with all 12 covariates included and correspond to the results of Table 3 columns 1 and 5. Each intermediate point represents one β_1 estimate using a unique vector of covariates.

The coefficients are generally robust to differing sets of covariates. When estimating the effect of a light truck rather than a car on pedestrian death probability, any three covariates can be removed and the result remains statistically significant at the 5% level. For front-end height, any five covariates can be removed, and the vehicle weight result is significant under any set of covariates.

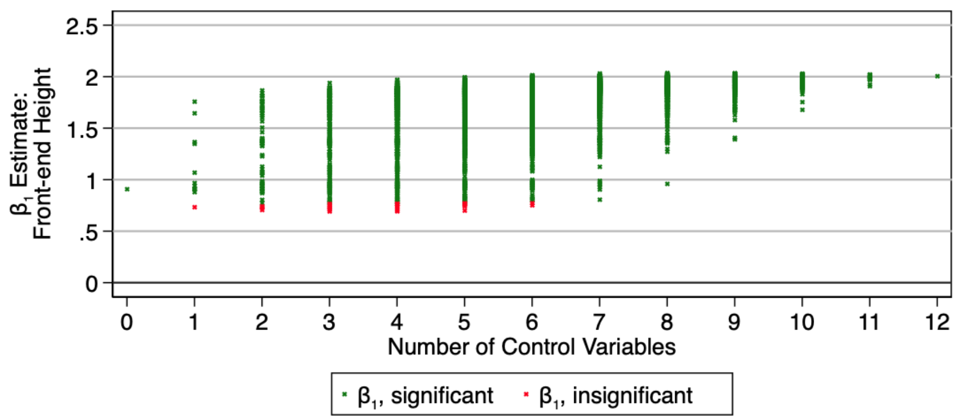
Examining the regressions that produce insignificant results, I find that including variables for whether the crash happened in daylight hours and controls for the speed of the vehicle are the most important variables for identifying a significant vehicle size effect. The inclusion of some control variables may be necessary to isolate the causal effect, given differences in crash characteristics, and a relatively small sample size.

Figure B1: Robustness to Control Variables Included

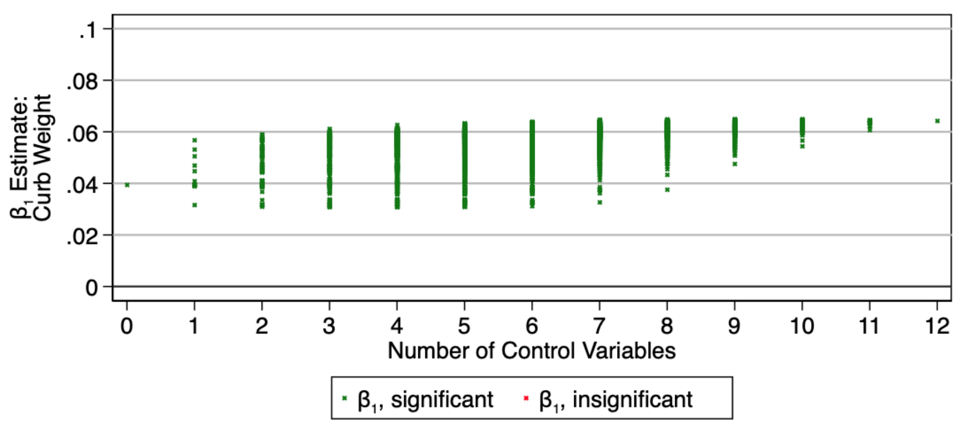
i. Light Truck Effect Estimate Across Different Sets of Covariates



ii. Front-end Height Effect Estimate Across Different Sets of Covariates



ii. Curb Weight Effect Estimate Across Different Sets of Covariates



Each subfigure displays 4,096 β_1 estimates, each pertaining to a separate regression. The number of covariates included are varied from left to right.

Appendix C: Effect of CRSS Crash Probability Weights

In the main analysis of this paper, I make use of the sampling weights provided in the CRSS data. Some crash types are intentionally oversampled in the data collection process and the weights are intended to allow for an analysis that approximates a nationally representative sample. As I use a selected subsample of data, the sampling weights may not properly approximate a nationally representative sample. In Table C1, I provide the main regression results of this paper (analogous to Table 3) but do not use the sample weights. I find very similar results regardless of whether sample weights are used, providing evidence that the choice to use weights is not important to the findings.

Table C1: Effect of Vehicle and Crash Characteristics on Pedestrian Death Probability: Unweighted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Light truck	0.497**						
	(0.141)						
Compact SUV		0.364		0.201		-0.095	-0.067
		(0.207)		(0.215)		(0.271)	(0.277)
Full-size SUV		0.752**		0.271		0.084	-0.004
		(0.276)		(0.349)		(0.388)	(0.396)
Pickup truck		0.598**		0.167		-0.067	-0.131
		(0.200)		(0.274)		(0.312)	(0.323)
Van		0.261		-0.097		-0.390	-0.417
		(0.304)		(0.343)		(0.404)	(0.404)
Vehicle weight (100 kgs)			0.071**	0.058*			0.031
			(0.017)	(0.027)			(0.033)
Front end height (meters)					1.967**	2.197**	1.641
					(0.441)	(0.842)	(1.045)
Travel speed (mph)	0.107**	0.108**	0.108**	0.109**	0.107**	0.108**	0.108**
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Travel speed squared (mph)	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Posted speed limit (mph)	0.028**	0.028**	0.028**	0.028**	0.028**	0.027**	0.027**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Alcohol involved	0.125	0.135	0.136	0.138	0.122	0.124	0.128
	(0.194)	(0.194)	(0.193)	(0.193)	(0.194)	(0.193)	(0.193)
Daylight conditions	-1.090**	-1.082**	-1.099**	-1.088**	-1.109**	-1.095**	-1.095**
	(0.177)	(0.179)	(0.179)	(0.181)	(0.180)	(0.181)	(0.181)
Clear weather conditions	-0.045	-0.052	-0.043	-0.048	-0.043	-0.050	-0.048
	(0.157)	(0.157)	(0.158)	(0.157)	(0.157)	(0.157)	(0.157)
Urban environment	0.000	0.024	0.010	0.024	0.001	0.015	0.017
	(0.213)	(0.216)	(0.216)	(0.217)	(0.217)	(0.219)	(0.219)
Driver gender (female=1)	-0.029	-0.011	0.009	0.003	-0.010	-0.021	-0.012
	(0.148)	(0.152)	(0.148)	(0.152)	(0.149)	(0.152)	(0.151)
Pedestrian gender (female=1)	0.479**	0.490**	0.494**	0.495**	0.495**	0.502**	0.502**
	(0.145)	(0.146)	(0.146)	(0.146)	(0.146)	(0.147)	(0.147)
Driver age	-0.003	-0.003	-0.003	-0.003	-0.004	-0.003	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Under 18 pedestrian	-1.008**	-0.991**	-0.991**	-0.997**	-1.017**	-1.016**	-1.013**
	(0.360)	(0.355)	(0.358)	(0.354)	(0.358)	(0.353)	(0.353)
Over 65 pedestrian	0.753**	0.752**	0.767**	0.758**	0.756**	0.752**	0.755**
	(0.162)	(0.162)	(0.162)	(0.162)	(0.163)	(0.163)	(0.163)
Crash year fixed effects	Y	Y	Y	Y	Y	Y	Y
N	3375	3375	3375	3375	3375	3375	3375

Significance levels: $*$: 5% $**$: 1%. Robust standard errors are shown in parenthesis. Regressions are estimated without sampling probability weights.

Appendix D: Effect of Large Vehicles on Cyclists

This paper focuses on the effect of large vehicles on pedestrian safety. However, cyclists are another category of road users that may be vulnerable to large vehicles for a similar set of reasons. Across the CRSS data, I identify 3,239 crashes that involve one vehicle and one cyclist and also have a complete set of crash covariates. The sample size is only slightly lower than the 3,375 pedestrian-involved crashes identified. However, while I identify 308 crashes where a pedestrian dies, I only observe 61 crashes where a cyclist dies. As a result, the sample variation may be too small to reliably estimate the effect of vehicle characteristics on cyclist death probability. Table D1 shows the main regression results but for cyclist incidents. I find some evidence that larger vehicles are more dangerous for cyclists.

Table D1: Effect of Vehicle and Crash Characteristics on Cyclist Death Probability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Light truck	0.688*						
	(0.334)						
Compact SUV		0.284		0.221		0.099	0.101
		(0.419)		(0.462)		(0.655)	(0.674)
Full-size SUV		-1.276		-1.447		-1.557	-1.574
		(0.872)		(0.972)		(1.039)	(0.979)
Pickup truck		1.364**		1.209		1.082	1.069
		(0.432)		(0.641)		(0.791)	(0.726)
Van		1.828*		1.707		1.591**	1.583*
		(0.889)		(1.024)		(0.611)	(0.681)
Vehicle weight (100 kgs)			0.071*	0.020			0.005
			(0.033)	(0.055)			(0.098)
Front end height (meters)					2.269	0.927	0.833
					(1.444)	(2.561)	(3.846)
Travel speed (mph)	0.186**	0.192**	0.185**	0.192**	0.186**	0.192**	0.192**
	(0.039)	(0.039)	(0.039)	(0.039)	(0.038)	(0.039)	(0.039)
Travel speed squared (mph)	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Posted speed limit (mph)	0.034	0.034	0.036	0.034	0.034	0.033	0.033
	(0.023)	(0.024)	(0.023)	(0.024)	(0.024)	(0.024)	(0.025)
Alcohol involved	1.238**	1.321**	1.226**	1.315**	1.223**	1.313**	1.312**
	(0.428)	(0.448)	(0.427)	(0.447)	(0.429)	(0.450)	(0.448)
Daylight conditions	-0.373	-0.294	-0.318	-0.279	-0.357	-0.287	-0.284
	(0.342)	(0.363)	(0.332)	(0.368)	(0.343)	(0.353)	(0.378)
Clear weather conditions	-0.425	-0.425	-0.442	-0.420	-0.440	-0.420	-0.419
	(0.360)	(0.382)	(0.363)	(0.384)	(0.358)	(0.374)	(0.381)
Urban environment	0.314	0.482	0.342	0.502	0.300	0.478	0.483
	(0.545)	(0.585)	(0.536)	(0.576)	(0.536)	(0.588)	(0.591)
Driver gender (female=1)	0.498	0.796*	0.511	0.794*	0.516	0.793*	0.792*
	(0.325)	(0.350)	(0.327)	(0.350)	(0.335)	(0.348)	(0.349)
Cyclist gender (female=1)	0.091	-0.036	0.026	-0.040	0.054	-0.036	-0.037
	(0.401)	(0.432)	(0.401)	(0.432)	(0.401)	(0.432)	(0.431)
Driver age	-0.019*	-0.023*	-0.020*	-0.023*	-0.019*	-0.023*	-0.023*
	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)
Under 18 cyclist	-0.675	-0.613	-0.607	-0.601	-0.609	-0.591	-0.590
	(0.605)	(0.612)	(0.606)	(0.617)	(0.599)	(0.601)	(0.604)
Over 65 cyclist	0.686	0.819*	0.703*	0.825*	0.705*	0.828*	0.829*
	(0.352)	(0.372)	(0.354)	(0.374)	(0.353)	(0.366)	(0.369)
Crash year fixed effects	Y	Y	Y	Y	Y	Y	Y
N	3239	3239	3239	3239	3239	3239	3239

Significance levels: $*$: 5% $**$: 1%. Robust standard errors are shown in parenthesis. Regressions are estimated with sampling probability weights.