Pedestrian Deaths and Large Vehicles

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Abstract

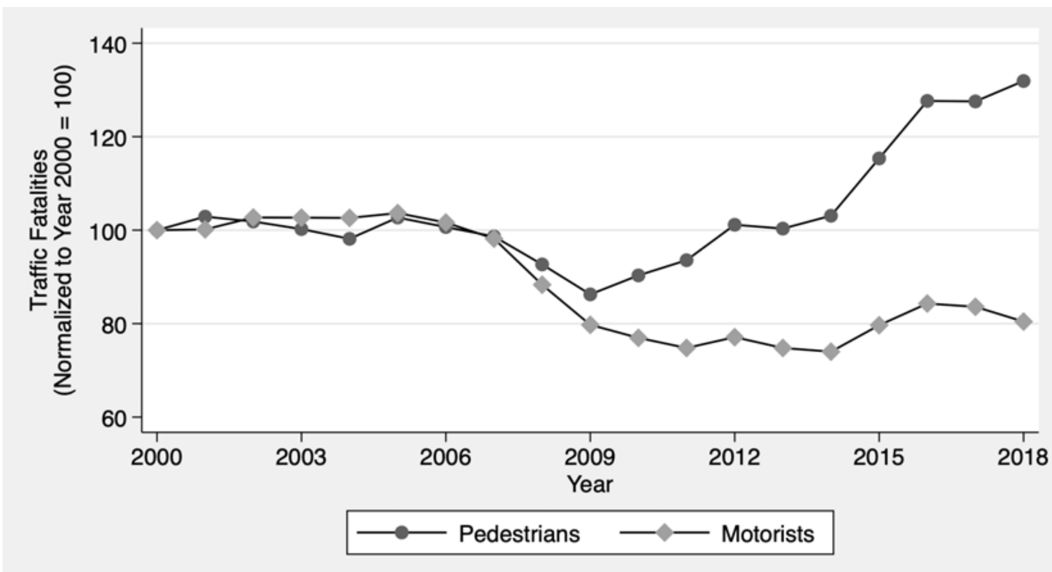
Traffic fatalities in the US have been rising among pedestrians even as they fall among motorists. Contemporaneously, the US has undergone a significant shift in consumer preferences for motor vehicles, with larger Sport Utility Vehicles comprising an increased market share. Larger vehicles may pose a risk to pedestrians, increasing the severity of collisions. I use data covering all fatal vehicle collisions in the US and exploit heterogeneity in changing vehicle fleets across metros for identification. Between 2000 and 2018, I estimate that replacing the growth in Sport Utility Vehicles with cars would have averted 1,100 pedestrian deaths. The largest Sport Utility Vehicles appear particularly culpable for pedestrian deaths.

Transportation; Safety; Health; Traffic Fatalities; Externalities
I1; R41; R42; R48

1 Introduction

Between 2000 and 2018, motor vehicle crashes killed 724,000 people in the US including 94,000 pedestrians.[1] Figure 1 charts the trends in traffic fatalities for both vehicle occupants and pedestrians over the 2000-2018 period. While deaths among motorists have declined over this period, deaths among pedestrians have risen by 32%. Over the same period the consumer market for private vehicles has shifted towards larger vehicles and particularly towards Sport Utility Vehicles (SUVs). Larger vehicles may impose a negative externality on pedestrians by making crashes involving pedestrians more lethal. I estimate the effect of large vehicle uptake on the pedestrian fatality rate.

Figure 1: Trends in Traffic Fatalities



The number of fatalities among drivers and their passengers fell by 20% between 2000 and 2018. Over the same period the number of motor vehicle related fatalities among pedestrians increased by 32%.

Vehicles on US roads became measurably larger between 2000 and 2018. Figure 2 plots changes in vehicle characteristics among all vehicles involved in a fatal crash between 2000 and 2018. While in 2000, the typical vehicle weighed 1,744 kg, by 2018 the average vehicle had increased in weight by 10% to 1,921 kg (Figure 2A). Additionally, SUVs increased their prevalence from 10.8% of vehicles to 19.7% (Figure

[1]National Highway Traffic Safety Administration, Fatality Analysis Reporting System.

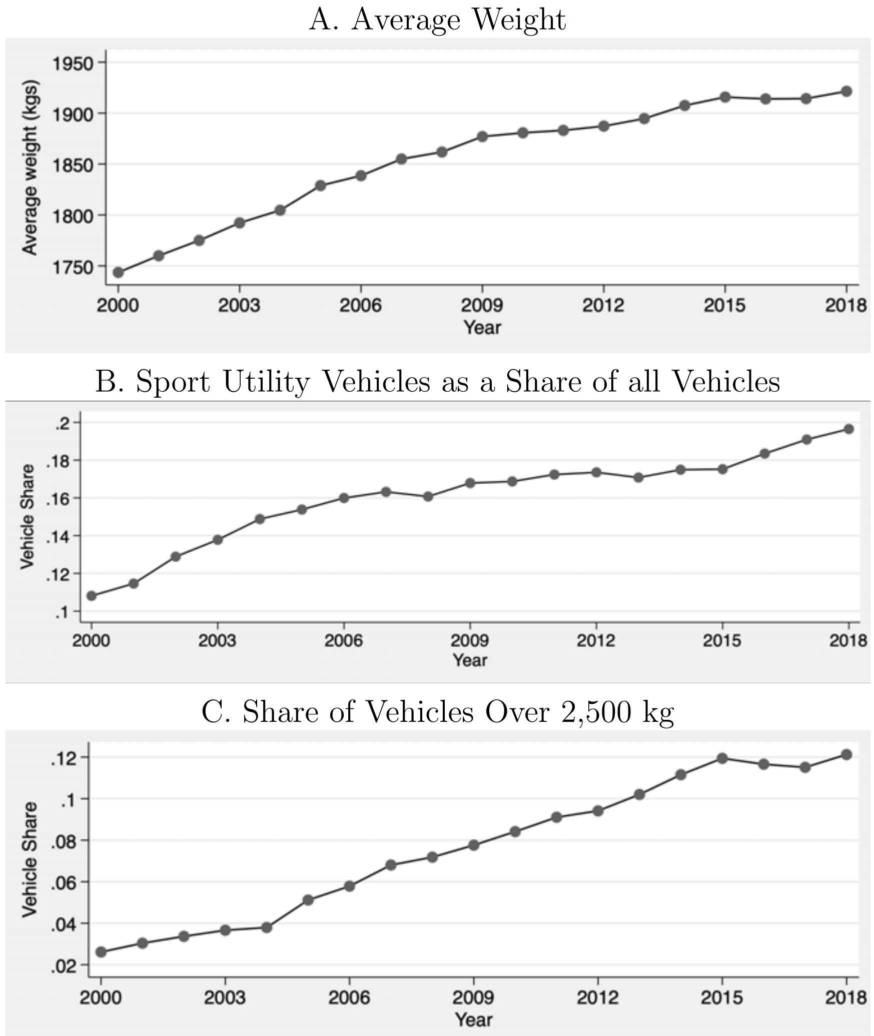
2B). Over this same period, a new class of very large vehicles began to enter the consumer market. In 2000 only 2.6% of vehicles involved in fatal crashes weighed more than 2,500 kg, by 2018 the share had increased fivefold to 12.1% (Figure 2C).[2] The increased prevalence of these very large vehicles was mostly attributable to the popularity of a few large SUVs, particularly the Ford Expedition and the Chevrolet Suburban and Tahoe.

While larger vehicles are designed to protect their drivers and passengers in the event of a crash, less concern is given to the effect on pedestrians. Past research in the safety literature has considered the mechanisms that relate vehicle size to motorist and pedestrian safety. There are two primary mechanisms that could lead large vehicles to generate additional harm when hitting a pedestrian. First, the additional weight means the vehicle will take longer to come to a stop and will strike with more force as compared to a lighter vehicle. Second, large vehicles have higher front ends, affecting the point of impact on a pedestrian. A conventional car is likely to strike a pedestrian in the legs, propelling them over the hood of the vehicle. A vehicle with a higher front end is likely to make first contact with the pedestrian's torso or head, harming vital organs and deflecting their body under the vehicle. In transportation safety literature, pedestrians hit by light trucks (a category including SUVs, pickups and minivans) have been found to suffer greater rates of mortality (Simms and Wood, 2006; Tamura et al., 2008) and higher rates of brain injury (Roudsari et al., 2004) than those hit by cars. Lefler and Gabler (2004) used US data from the 1990s to estimate that a pedestrian struck by a light truck is two to three times more likely to die than a pedestrian struck by a car. In a meta-analysis of papers concerned with pedestrian fatalities, Desapriya et al. (2010) found that the chance of fatal injury among pedestrians was 50% higher when struck by a light truck compared to a car. I will test for the effect of both vehicle weight and body type on pedestrian fatalities.

Significant past research has examined the effect of vehicle size on road safety. The adoption of the Corporate Average Fuel Economy (CAFE) vehicle emission standards in the US encouraged consumers to purchase lower emission vehicles, which were likely to be smaller. Crandall and Graham (1989) argued that this incentive resulted in higher rates of motorist fatalities due to smaller vehicles providing more limited protection to drivers. The authors pointed out that drivers of smaller vehicles are more vulnerable in crashes than they would be in a larger vehicle and extrapolate

[2] Data comes from the national Fatality Analysis Reporting System and the Environmental Protection Agency's Fuel Economy Test Car List Database. Data details are included in Section 2.

Figure 2: Changes in Vehicle Size Among Vehicles Involved in a Fatal Crash



Between 2000 and 2018 the average weight of consumer vehicles involved in a fatal crash increased by 10%, the prevalence of SUVs increased by 78% and the share of vehicles that are more than 2,500 kg increased by 363%.

this effect across the market. However, this method ignores external safety risks that larger vehicles may impart by increasing the severity of injury to other motorists and to pedestrians. Focusing on a subset of crashes from the 1990s, Toy and Hammitt (2003) estimated the effect of vehicle types on injury severity in the US. Results indicated that SUVs fared better in protecting their driver in the event of a crash, but also inflicted more damage onto the drivers of other vehicles compared to cars. Further analysis of the interaction between light trucks in cars is provided in Gayer

(2004), who similarly argued that the driver safety improvements provided by large vehicles may come at the expense of externally imposed risks. Estimates suggested that an increase in light trucks would increase overall traffic fatalities. Van Ommeren et al. (2013) focused on the relative weights of opposing vehicles involved in collisions in the Netherlands, estimating that a 500 kg increase in one car's weight increased the risk of a fatality by 70%. Ahmad and Greene (2005) revisited the analysis of Crandall and Graham (1989) specifically, finding little evidence that CAFE led to higher road fatalities in aggregate.

White (2004) attempts to directly estimate the marginal effect of drivers switching from smaller to larger vehicles in the US during 1995-2001. The assessment showed that for every driver whose life was saved on account of being in a larger vehicle 4.3 fatalities were created among other drivers, pedestrians and cyclists. The paper also points out the inability of the legal system to provide incentives for drivers to internalize external safety risks, as drivers are typically only held responsible in cases of driver negligence rather than being held responsible for total damages inflicted.

Anderson (2008) examined cross state variation in light truck prevalence and traffic fatalities spanning the 1981-2004 period in the US. The author found that states with higher rates of light truck use had higher rates of traffic fatalities and that the increase in fatalities was primarily due to an increase in deaths among drivers and pedestrians who were struck by a light truck rather than a smaller vehicle. Anderson and Auffhammer (2014) quantified the safety externality of large vehicles, arguing the US vehicle fleet is inefficiently large and the externality could be corrected through gasoline taxes. Li (2012) also attempted to quantify the externality of light trucks, estimating the implied road safety externality of a light truck over its lifetime to be $2,400.

While there are several past studies linking vehicle size and safety, the current study is unique in a number of respects. First, I contribute an analysis covering a much more recent period in the US. The characteristics of the vehicle fleet have changed substantially during the 2010s. Second, I focus on the effect of vehicle size on pedestrian fatalities in particular. The sharp increase in pedestrian fatalities in the US is a recent phenomenon that has not been noted or studied in the economics literature. Third, I provide a new and novel data source by combining vehicle weight data from the Environmental Protection Agency (EPA) with crash level data and vehicle registration data that allows for analysis at the metropolitan level. Fourth, while prior studies have focused on vehicle weight, I focus on differences in vehicle body types, finding that large SUVs are particularly culpable for rising pedestrian deaths, even conditional on weight.

The relationship between vehicle characteristics and pedestrian fatalities is one element of overall road safety. Significant economic research has been undertaken to investigate other causes of traffic fatalities such as vehicle speed (Ang et al., 2020; Van Benthem, 2015), road congestion (Green et al., 2016) alcohol consumption (Baughman et al., 2001; Green et al., 2014; Hansen, 2015; Jackson and Owens, 2011; Levitt and Porter, 2001; Ruhm, 1996), public policy and regulation (Basili and Belloc, 2020; Borsati et al., 2019; Bourgeon and Picard, 2007; Carpenter and Stehr, 2008; Karaca-Mandic and Ridgeway, 2010; Peltzman, 1975), electronic distractions (Blattenberger et al., 2013; Oviedo-Trespalacios, 2018) and the driver's state of mind (Giulietti et al., 2020). The current study is focused specifically on the effect of vehicle characteristics on pedestrian fatalities.

The paper will proceed as follows. Section 2 provides information on data sources. Section 3 discusses the regression methodology. Section 4 provides results and Section 5 will conclude.

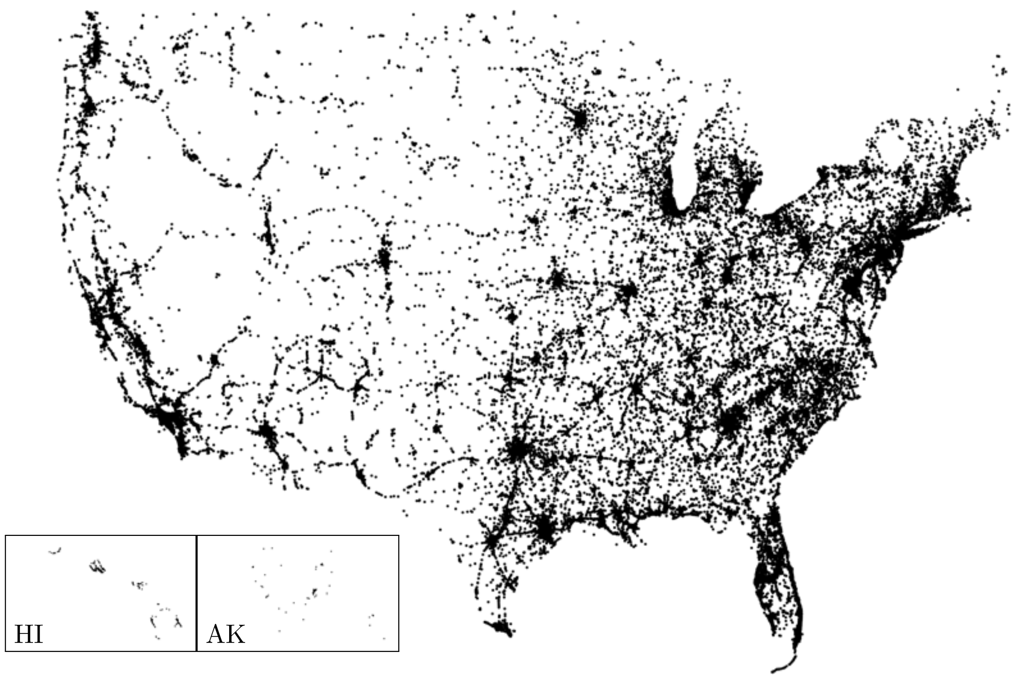
2 Data

I combine data from a number of public sources. Traffic fatality data is taken from the National Highway Traffic Safety Administration (NHTSA), Fatality Analysis Reporting System (FARS). The data set is a complete record of all fatal traffic collisions in the US. To be included in the data the collision must have been on a public road, involved any type of motor vehicle and caused the death of one or more individuals.[3] The database contains a large number of variables characterizing the collision, including information on all vehicles and persons that were involved in the incident. The study period will cover 2000 to 2018. During this period FARS recorded 658,000 crashes that resulted in at least one fatality. These crashes included 994,000 vehicles and 1,672,000 individuals. 102,000 of the individuals were pedestrians. 724,000 individuals, including 94,000 pedestrians, died due to a crash. The enormous number of fatalities underlines the scope of the public health issue. The national distribution of crashes causing a pedestrian fatality are shown in Figure 3. Incidents

[3] To be considered as caused by the vehicle crash, the death must occur within 30 days of the collision.

cover all populated areas of the US, and are concentrated in city centers as well as extending along the interstate highway system. In the main analysis I analyze only crashes occurring within metropolitan areas, defined according to Core Based Statistical Area (CBSA) boundaries.

Figure 3: All US Pedestrian Fatalities 2001-2018



Each dot corresponds to a vehicle crash that resulted in at least one pedestrian fatality. The year 2000 is included in analysis but not in this figure as observations from 2000 lack latitude and longitude information.

The empirical analysis will base estimates on the rate of deaths per 100,000 residents across metropolitan areas. The sample contains all metropolitan areas in the US for which data is available.[4] The final data set is a balanced panel containing 362 US metropolitan areas with annual observations spanning 2000-2018. Every incident recorded in the FARS data is accompanied by precise location information. I use the recorded county of the crash to assign each observation to a metropolitan area. Across all years and metros, the average rate of traffic fatalities was 13.3 deaths per 100,000 residents. The death rate among vehicle drivers and passengers was 11.8 per 100,000

[4]Four metros were dropped. The metropolitan areas of Aimes, Iowa; Carson City, Nevada; Fairbanks, Alaska; and Sandusky, Ohio were dropped because they had no fatal crashes that could be merged to EPA vehicle weight data in at least one year of analysis.

while the rate of pedestrian deaths was 1.5 per 100,000. Summary statistics are provided in Table 1.

For each metropolitan area in the US I construct annual estimates of vehicle fleets by vehicle body type, relying on both FARS data and vehicle registration data. FARS includes variables on vehicle body type. In the average metro, 46.3% of consumer vehicles involved in a fatal crash were cars while 42.5% were light trucks and 11.1% were motorcycles. I examine the subgroups within the light truck category, including SUVs (16.1% of vehicles), pickup trucks (20.2%) and minivans (6.1%). I further brake down the SUV category into Small SUVs (12.2%) and Large SUVs (3.9%). Large SUVs are defined by FARS to be “full-size multi-purpose vehicles primarily designed around a shortened pickup truck chassis.” I also include the FARS category of “Utility Station Wagon” in my definition of Large SUVs.[5] Utility Station Wagons have a similar body type to Large SUVs but are typically even larger, including an extended passenger area. Identifying Large SUVs will be important as these vehicles are likely to have body designs that include very high front ends, which safety tests have suggested could lead to increased pedestrian mortality. The most common Large SUVs in the data are the Chevrolet Tahoe and Chevrolet Suburban, which make up 24% and 15% of Large SUVs respectively.

When computing metropolitan vehicle fleet shares I focus on consumer vehicle shares, omitting the FARS vehicle category for commercial buses and heavy trucks. Heavy trucks are classified as those exceeding 4,536 kg (10,000 pounds) and account for 9.2% of vehicles involved in fatal crashes over the study period. I also omit crashes involving vehicles that fall outside of the typical categories, including construction and farm equipment, golf carts, and snowmobiles. These unclassified vehicles comprised 1.7% of all vehicle observations.

In addition to vehicle characteristics I use FARS data to derive a set of control variables. For each metropolitan area and year I derive the average model year of a vehicle involved in a crash, the average age of a driver and the share of crashes that

[5]The Large SUV and Utility Station Wagon categories in FARS data includes the following vehicle models: Acura MDX; AMC Hummer; Avanti Studebaker XUV; Buick Enclave (2013 on); Cadillac Escalade/Escalade ESV; Chevrolet Full-size Blazer/Suburban/Tahoe/Travellall/Traverse (2013 on)/Yukon XL (2000 on); Chrysler Aspen; Dodge Durango (2004 on); Ford Full-size Bronco (1978 on)/Expedition/Excursion; GMC Acadia (2013 on)/Jimmy (1991-1994)/Yukon (Denali/XL); Honda Pilot; Hyundai Veracruz (2008 on); Infiniti QX56/QX80; Isuzu Ascender; Jeep Grand Cherokee/Grand Wagoneer; Kia Mesa/Borrego; Land Rover LR2/LR3/Freelander (2004 on)/Range Rover; Lexus LX450/470; Lincoln Navigator; Mazda CX-9; Mercedes Benz GL; Nissan Armada; Porsche Cayenne; Toyota Land Cruiser/Sequoia; and Volkswagen Touareg.

involved a drunk driver. Average values for these control variables are shown in Table 1.

Table 1: Metropolitan Summary Statistics

Variable	Mean	Standard Deviation	Min	Max
Pedestrian deaths per 100,000	1.523	0.754	0.266	5.797
Motorist deaths per 100,000	11.851	4.467	3.37	34.717
Average model year	1999.7	0.936	1996.5	2001.7
Drunk driver related	0.290	0.058	0.124	0.502
Average driver age	41.281	1.882	35.269	47.779
Car share	0.510	0.062	0.28	0.697
Light truck share	0.454	0.058	0.310	0.642
SUV share	0.185	0.028	0.105	0.282
Small SUV share	0.141	0.025	0.081	0.241
Large SUV share	0.045	0.016	0.009	0.114
Pickup share	0.189	0.058	0.043	0.393
Minivan share	0.078	0.018	0.031	0.126
Motorcycle share	0.033	0.016	0.010	0.168
Average vehicle weight (kg)	1,850	60	1,735	2,068

N = 6,878. Data is at the CBSA-year level. Each of the 362 CBSAs in the data set have 19 observations, one for each year in 2000-2018. Vehicle shares are shown with state level vehicle registration data adjustments.

To construct vehicle fleet shares at the metropolitan level, I augment FARS data with annual data on all vehicles registered in the US from the Federal Highway Administration (FHWA) Highway Statistics data set. The data contains the number of vehicles registered in each state, broken out by vehicle type. The FHWA state registration data includes categories for light trucks, SUVs, pickup trucks, minivans and motorcycles which are consistent with the FARS definitions. The distinction between “Small” and “Large” SUVs that is made in the FARS data is not available in the FHWA data. Annual reports from FHWA cover all years of analysis. I make use of registration data to account for the possibility that different vehicle types may be over or under represented in fatal crash data.

While prior studies have focused on state level variation, I choose to focus on the metropolitan area as the unit of analysis. The use of a smaller unit of geography allows estimates to be based on a larger set of observations that preserves more spatial variation in the data. There is significant heterogeneity in variables across metros within the same state, suggesting state level analysis may be masking important variation. Relevant transportation system differences are more likely to be homogenous within metros than states as metro residents share the same transportation infrastructure for commuting and daily travel. The use of fixed effects and control variables at the metropolitan level will allow for differences in metro characteristics to be closely controlled for in regressions.

One limitation of conducting analysis at the metro level is that vehicle registration data is not available at levels below the state. If estimates of metro vehicle fleets are derived from crash data, the estimated fleet shares may be biased if particular vehicle types are more likely to be involved in fatal vehicle crashes. In order to correct for this bias I revise metro fleet share estimates derived from crash data according to the disparity between vehicle shares from registration data and crash data. Table 2 compares the vehicle shares from the FARS crash data, with the national FHWA vehicle registration data. The largest discrepancy is the stark overrepresentation of motorcycles in fatal crashes. While only 3.0% of vehicles registered nationally are motorcycles, 10.6% of vehicles involved in fatal crashes are motorcycles. For light trucks, I find that 44% of vehicles registered nationally are light trucks, while 42% of vehicles involved in fatal crashes are light trucks. Table 2 suggests that vehicle shares derived from crash data are relatively representative of the vehicle fleet at the national level.

To correct metro vehicle share estimates I calculate the over and under representation of vehicle shares in crash data relative to registration data. National data suggests that cars are underrepresented in fatal crash data by 11.0%, SUVs are underrepresented in crash data by 14.1%, pickups are overrepresented by 14.2%, minivans are underrepresented by 24.7% and motorcycles are overrepreseted by 253.3%. These gaps could be the result of particular vehicle types being intrinsically less safe, or the gaps could be due to the characteristics of the drivers who choose particular vehicle types. I first derive nationally adjusted estimates of metro vehicle fleets by assuming that the different propensity to be involved in a fatal crash across vehicle types is uniform across the US. For example, if a metropolitan area reported that 20.0% of vehicles involved in fatal crashes for a particular year were SUVs, I assume 22.8% of the vehicle fleet were SUVs in that year. The methodology allows me to generate metro level vehicle fleet estimates that account for the differing crash propensity across vehicle types. The necessary assumption is that differences in fatal crash likelihood across vehicle types are identical across metros. In the main specification, I calculate over and under representation rates at the state level rather than the national level. Using state specific adjustments further weakens the necessary assumption to be that the crash propensity across vehicle types is identical across metros in the same state. For metros that span multiple states I use population weighted data from the relevant states to estimate vehicle registration shares. Because FHWA does not distinguish between Large and Small SUVs I assume that, within the SUV category, Large and Small SUV shares in crash data are representative of fleet shares. Adjusted vehicle fleet shares are summarized in Table 1.

I find that adjusting fleet shares by crash likelihood does not substantially affect results because the vehicle shares derived from FARS are in fact fairly representative of the overall vehicle fleet, with the exception of motorcycles. I will test for sensitivity of results to differing vehicle fleet adjustments (Section 4).

Table 2: Vehicle Shares by Data Source

	FARS Metros Only	**FARS National**	**FHWA Registrations National**
Car share	0.479	0.470	0.528
Light truck share	0.412	0.424	0.442
SUV share	0.159	0.159	0.185
Pickup share	0.189	0.201	0.176
Minivan share	0.062	0.061	0.081
Motorcycle share	0.108	0.106	0.030

FARs data is a selective sample of vehicles that have been involved in a crash that resulted in a fatality. FHWA data covers all registered vehicles nationally. The data from both sources covers 2000-2018. Fleet shares from the two sources are relatively consistent, with the exception of motorcycles.

FARS data includes the make, model and model-year of every vehicle involved in an incident. Using this information I merge on vehicle weight data from the EPA fuel economy testing data. I am able to match EPA vehicle weights to 82.1% of FARS vehicle observations. The EPA data includes information for every vehicle that underwent EPA testing across model years. Data is available from 1984 to present. The FARS observations that cannot be matched to EPA data include vehicles manufactured prior to 1984 (2.4% of FARS observations) as well as cases where the vehicle make and model have no corresponding entry in the EPA data set (15.6% of FARS observations). The latter case is due to the inconsistent classifications of vehicles between the NHTSA and the EPA. For example, different assumptions are made regarding when two slightly different versions of a vehicle should be considered as different models. There are some cases were the EPA data has information on a particular make and model but not for all years. In such cases I assume the vehicle weight is the same as the most recent model year for which data is available. A significant amount of manual coding was required so that these data sets could be merged reliably.

Regressions will control for changes in economic and demographic conditions through time, across metros. I use demographic variables from the US Census (2000) and from the American Community Survey (2008-2012 5-year estimates and 2014-2018 5-year estimates). The data is available at the county level which I collapse to the CBSA level. I linearly interpolate the data to convert the reported data into annual estimates. I also control for variation in metropolitan GDP across the study period. I use the Bureau of Economic Analysis (BEA) county level GDP data. The data set includes GDP estimates for the US between 2002 and 2018. I linearly extrapolate the GDP estimates to impute values for 2000 and 2001. Due to the use of metropolitan fixed effects and the relatively gradual change in metropolitan demographic and economic conditions, results prove to be insensitive regarding the inclusion of control variables. I show this empirically in Appendix A.

3 Methodology

US metros differ in the average characteristics of their vehicle fleets and have experienced heterogeneous adoption of light trucks and large vehicles over the study period. I estimate the impact of vehicle fleet characteristics on road deaths by regressing the metropolitan pedestrian fatality rate against several measures of vehicle fleet characteristics. Estimation of the relationship in a panel regression allows for the inclusion of metropolitan fixed effects, which absorb time invariant heterogeneity between metros that may be correlated with both fleet characteristics and fatality rates.

Equation 1 captures the regression equation for estimating the effect of average vehicle weight. D_{mt} is the number of deaths per hundred thousand people, where m indexes a particular metro and t indexes a particular year. W_{mt} is the average weight of a vehicle for a particular metro-year observation. Ψ_{mt} is a vector of metro-year control variables. Φ_m is a vector of metro fixed effects and Λ_t is a vector of year fixed effects. The use of year fixed effects will control for national trends through time. I cluster errors at the metro level in all specifications.

$$D_{mt} = \beta_0 + \beta_1 W_{mt} + \Psi_{mt} + \Phi_m + \Lambda_t + \varepsilon_{mt} \tag{1}$$

I include an array of control variables in Ψ_{mt}. From FARS data I include control variables for the average model year of the vehicle fleet, the average age of a driver and the share of crashes where alcohol was a factor. Controlling for the average age of the vehicle fleet provides a proxy for vehicle characteristics and safety features that change through time. From US Census sources I include control variables for metropolitan population, population density, the share of local residents with a high school education, the share of local residents with a college education, the median household income, race and ethnicity shares (white, Black, Asian, Hispanic), and the share of the local population who are male. From BEA data I include a control variable for metropolitan GDP.

Equation 2 is used to estimate the impact of vehicle fleet shares on the pedestrian fatality rate. When constructing vehicle fleet shares, all vehicles fall into categories of either cars, light trucks or motorcycles. Within the light truck category there are SUVs, pickups and minivans. Within the SUV category I further distinguish between Large and Small SUVs. Equation 2 is composed similarly to Equation 1 but rather than using vehicle weight I use the share of a metro's vehicle fleet in each category for a particular year. In the basic form, I include variables for light truck share (L_{mt}) and motorcycle share (C_{mt}). The omitted category is cars. This model setup allows β_1 to be interpreted as the effect of converting a share of cars to light trucks on pedestrian fatalities. For example $0.1 \times \beta_1$ is the effect of converting 10% of the local vehicle fleet from cars to light trucks on the pedestrian fatality rate. I also perform regressions that are analogous to Equation 2 but where I break out the light truck category into the more disaggregated categories.

$$D_{mt} = \beta_0 + \beta_1 L_{mt} + \beta_2 C_{mt} + \Psi_{mt} + \Phi_m + \Lambda_t + \varepsilon_{mt} \tag{2}$$

A central concern with arriving at causal estimates will be the possible presence of omitted variable bias. There may exist unobserved metropolitan characteristics that are correlated with both road fatalities and vehicle ownership choices. For example, metros with wide roads or many highways may provide an incentive for owning a larger vehicle but this type of road infrastructure may directly contribute to road deaths by accommodating higher vehicle speeds (Lewis-Evans and Charlton, 2006; Manuel et al., 2014). Metropolitan fixed effects control for any omitted variables across metros that are time invariant. Supportive of the identification strategy is the fact that, while metropolitan characteristics such as urban form and road characteristics evolve slowly, the shift towards larger vehicles has happened relatively quickly over the study period. If vehicle fleet characteristics contribute to pedestrian fatalities I expect to find that metros that had different shifts in vehicle fleets experienced different shifts in pedestrian fatalities. I control for a wide array of time varying metro characteristics to isolate this statistical relationship. I also provide a specification where I omit time varying metro characteristics (Appendix A). I find that the choice to include these controls has almost no effect on results, suggesting that omitted variable bias is not a significant concern for the specification (Oster, 2019). I also provide a robustness test where I control for the linear trends in pedestrian fatalities across metros, further isolating the effect of changing vehicle characteristics, and find results are robust (Appendix B).

An additional barrier to identification is the possibility of reverse causation. While larger vehicles may contribute to pedestrian fatalities for the reasons given above, rising traffic fatalities may cause local residents to look for ways to improve their road safety, potentially influencing their vehicle purchase decisions. This concern is less relevant to the study of pedestrian fatalities than it is for motorist fatalities. Motorists have a clear incentive to purchase a larger vehicle when confronted with deteriorating road safety among motorists. A changing pedestrian fatality rate is not likely to directly influence the decision of drivers regarding what vehicle to purchase, as the driver does not bear the risks imposed on pedestrians. However, pedestrian fatalities and motorist fatalities may be correlated. In a robustness check I will estimate Equations 1 and 2 while directly controlling for the rate of motorist fatalities, as a proxy for road safety. I find the results are robust to controlling for this variation.

4 Results

In this section I provide results from the panel regression models as well as results from robustness checks, alternative specifications and estimates of counterfactual scenarios. Table 3, Columns 1-5 show estimates of the effects of average vehicle weight and vehicle fleet shares on the annual number of pedestrian deaths per 100,000 population. In addition to metro and year fixed effects, regressions include the array of control variables listed in the previous section. I supply coefficient estimates for control variables in Appendix A. I adjust estimates of vehicle fleets using state level registration data, according to the method described in Section 2. Overall, I find that larger vehicle fleets are related to more pedestrian fatalities.

Table 3: Effect of Vehicle Characteristics on Pedestrian Fatality Rate

	(1)	(2)	(3)	(4)	(5)
Vehicle weight (100 kg)	0.036*				-0.001
	(0.015)				(0.019)
Light truck share		0.507**			
		(0.130)			
SUV share			0.348*		
			(0.163)		
Small SUV share				0.228	0.231
				(0.186)	(0.187)
Big SUV share				0.761*	0.769*
				(0.308)	(0.335)
Pickup share			0.507**	0.504**	0.512*
			(0.179)	(0.179)	(0.220)
Minivan share			0.507*	0.511*	0.515*
			(0.224)	(0.225)	(0.245)
Motorcycle share		-2.181**	-2.284**	-2.280**	-2.272**
		(0.566)	(0.570)	(0.571)	(0.594)
CBSA fixed effects?	Y	Y	Y	Y	Y
Year fixed effects?	Y	Y	Y	Y	Y
Control variables?	Y	Y	Y	Y	Y
R^2	0.052	0.058	0.057	0.058	0.058
N	6878	6878	6878	6878	6878

Significance levels: $*$: 5% $**$: 1%. Standard errors are shown in parenthesis and are clustered at the CBSA level. The dependent variable is the number of pedestrian fatalities per 100,000 population. Control variables include: population, population density, share of population with a high school diploma, share of population with a college degree, median household income, share of population who are white, share of population who are Black, share of population who are Asian, share of population who are Hispanic, share of population who are male, CBSA GDP, share of fatal crashes that involved alcohol, and average age of drivers involved in fatal crashes.

Column 1 regresses the pedestrian fatality rate against the average weight of vehicles involved in fatal crashes, following Equation 1. Every 100 kg increase in average vehicle weight is associated with an additional .04 fatalities per 100,000 residents. The median observation had an annual pedestrian fatality rate of 1.34 fatalities per 100,000 residents, meaning that a 100 kg increase in average vehicle weight is related to a 2.7% increase in pedestrian fatalities for a metro with the median fatality rate.

Table 3, Column 2 estimates the effect of light trucks. In columns 2-5 the omitted category is cars, so that the partial effects on vehicle types can be interpenetrated as the effect of substituting cars with the various vehicle categories. Converting 10% of vehicles from cars to light trucks is associated with an increase in the pedestrian fatality rate of .05, or a 3.8% increase for the median metro. Column 3 breaks out light trucks into the constituent categories. I find pickup trucks, minivans and SUVs all significantly increase pedestrian fatalities relative to cars, with point estimates suggesting that SUVs are the least harmful to pedestrians of the three light truck types. Converting 10% of the vehicle fleet from cars to pickups is estimated to increase the pedestrian fatality rate by .05 deaths per 100,000 residents (3.8% in the median metro). I find that converting 10% of cars to minivans has the same effect as converting to pickups. Converting 10% of cars to SUVs would increase pedestrian deaths by .03 deaths per 100,000, or 2.6% in the median metro. In column 4 I further break out SUVs into Large and Small SUVs. I find that Small SUVs have no significant effect, while the share of Large SUVs has a positive relationship with pedestrian fatalities, with an effect larger than that of pickups or minivans. Converting 10% of a metro's vehicle fleet from cars to Large SUVs increases the pedestrian fatality rate by .08 deaths (5.7% in the median metro).

Across specifications I find that the share of motorcycles has a highly significant, negative effect on pedestrian deaths. Motorcycles are commonly involved in fatal crashes, but in most cases the fatality is only the driver of the motorcycle and pedestrians are rarely victims of fatal crashes involving motorcycles.

Column 5, includes the four light truck categories and average vehicle weight in a single regression. Interestingly, conditional on vehicle types, vehicle weight appears to have no effect on the pedestrian fatality rate. However, conditional on weight, the presence of more light trucks, particularly Large SUVs, pickups and minivans, has a large and statistically significant effect on pedestrian fatalities. This result suggests that it is the dimensions and shape of large vehicles that contribute to pedestrian fatalities, not their weight *per se*. Prior research has largely used the weight of vehicles as a proxy for the externally imposed safety risk of large vehicles. In the case of pedestrian safety, results suggest that body type is more important than weight.

As discussed in Section 2, metropolitan fleet shares derived from crash data will be biased if particular vehicle types are involved in fatal crashes at different rates.

Table 4 tests the sensitivity of results to alternative vehicle share corrections. In columns 1-3 I estimate the effect of substituting cars for light trucks, repeating the Equation 2 specification. In column 1 I use unadjusted metro vehicle shares taken directly from FARS crash data. In column 2 I adjust vehicle shares according to their relative likelihood of being involved in a fatal crash by using a uniform adjustment based on the difference between national FARS statistics and national FHWA vehicle registration data. In column 3 I use adjustments based on state level differences in vehicle prevalence between the two data sources, matching the main specification. In columns 4-6 I estimate the effect of substituting cars for different light truck types, testing the sensitivity of results to the different vehicle fleet adjustments. I find that the estimates of vehicle shares on pedestrian fatalities are robust to differing approaches to correcting the bias associated with a vehicle type's propensity to be involved in a fatal crash. I do find that the adjustment has a significant effect on my estimate of motorcycles' effect of pedestrian fatalities, consistent with the large overrepresentation of motorcycles in crash data.

A concern with identification may be that if there existed time varying omitted variables that affected both road safety and vehicle choice this could lead to biased estimates. Also, issues with reverse causality could arise if drivers choose to purchase larger vehicles at times when road safety is deteriorating. Controlling for the motorist fatality rate should eliminate much of this bias by introducing a strong proxy for road safety conditions. On the other hand, motorist fatalities may be an inappropriate control variable because it is not exogenous to pedestrian fatalities. Table 5 compares regression results to an alternative specification where I add a control for the rate of motorist fatalities. Columns 1, 3 and 5 repeat the main regressions using the different levels of vehicle type aggregations. Columns 2, 4 and 6 add the additional motorist fatality rate control variable. The estimated effects of vehicle characteristics are almost identical regardless of whether motorist fatalities are controlled for. If omitted variable bias or reverse causation issues existed that were related to the general state of road safety I would expect main coefficient estimates to change substantially. This result provides additional evidence that the specification is able to isolate exogenous variation in the vehicle fleet that has a causal effect on the rate of pedestrian fatalities.

While all regressions include CBSA fixed effects, this would not control for the possibility that particular CBSAs have long run temporal trends that are correlated with both changing vehicle shares and changing road safety. Such trends would potentially bias estimates if they are not perfectly correlated with the included control

Table 4: Effect of Fleet Shares on Pedestrian Fatality Rate, Effect of Vehicle Share Adjustments

	(1)	(2)	(3)	(4)	(5)	(6)
Light truck share	0.469**	0.450**	0.507**			
	(0.141)	(0.135)	(0.130)			
SUV share				0.362	0.312	0.348*
				(0.190)	(0.163)	(0.163)
Pickup share				0.469**	0.537**	0.507**
				(0.172)	(0.196)	(0.179)
Minivan share				0.646*	0.488*	0.507*
				(0.276)	(0.208)	(0.224)
Motorcycle share	-1.009**	-3.535**	-2.181**	-1.020**	-3.573**	-2.284**
	(0.196)	(0.688)	(0.566)	(0.196)	(0.688)	(0.570)
Vehicle share adjustment:	None	National	State	None	National	State
CBSA fixed effects?	Y	Y	Y	Y	Y	Y
Year fixed effects?	Y	Y	Y	Y	Y	Y
Control variables?	Y	Y	Y	Y	Y	Y
R^2	0.060	0.060	0.058	0.060	0.060	0.057
N	6878	6878	6878	6878	6878	6878

Significance levels: $*$: 5% $**$: 1%. Standard errors are shown in parenthesis and are clustered at the CBSA level. The dependent variable is the number of pedestrian fatalities per 100,000 population. Control variables include: population, population density, share of population with a high school diploma, share of population with a college degree, median household income, share of population who are white, share of population who are Black, share of population who are Asian, share of population who are Hispanic, share of population who are male, CBSA GDP, share of fatal crashes that involved alcohol, and average age of drivers involved in fatal crashes.

variables. In Appendix B I provide an alternative specification where I add CBSA specific linear time trends. I find results are almost identical regardless of whether CBSA time trends are included.

I can use coefficient estimates to estimate counterfactual scenarios of alternative vehicle adoption. I use the regression coefficients from the most disaggregated regression (Table 3, column 4) to estimate the number of pedestrian fatalities that were caused by the presence of particular vehicle types, compared to the counterfactual scenario where those vehicles were replaced with cars. I multiply the estimated partial effects by the fleet share held by that vehicle type in each year and then scale the figure up by the overall population across all metros in the data set.

Figure 4 graphs the implied number of pedestrian fatalities caused by all of the light truck categories, compared to the counterfactual where all of these vehicles were

Table 5: Effect of Vehicle Characteristics on Pedestrian Fatality Rate, Controlling for Motorist Fatalities

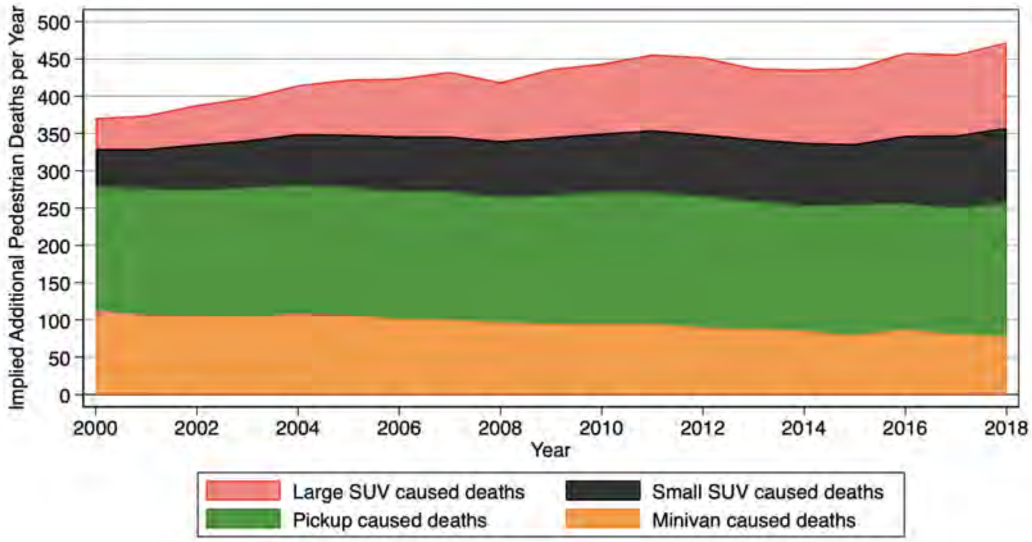
	(1)	(2)	(3)	(4)	(5)	(6)
Vehicle weight (100 kg)	0.036*	0.038*				
	(0.015)	(0.015)				
Light truck share			0.507**	0.519**		
			(0.130)	(0.129)		
SUV share					0.348*	0.349*
					(0.163)	(0.162)
Pickup share					0.507**	0.527**
					(0.179)	(0.179)
Minivan share					0.507*	0.517*
					(0.224)	(0.224)
Motorcycle share			-2.181**	-2.070**	-2.284**	-2.174**
			(0.566)	(0.564)	(0.570)	(0.568)
Motorist deaths per 100,000		0.016**		0.015**		0.015**
		(0.004)		(0.004)		(0.004)
Vehicle share adjustment:	State	State	State	State	State	State
CBSA fixed effects?	Y	Y	Y	Y	Y	Y
Year fixed effects?	Y	Y	Y	Y	Y	Y
Control variables?	Y	Y	Y	Y	Y	Y
R^2	0.052	0.055	0.058	0.061	0.057	0.060
N	6878	6878	6878	6878	6878	6878

Significance levels: $*$: 5% $**$: 1%. Standard errors are shown in parenthesis and are clustered at the CBSA level. The dependent variable is number of pedestrian fatalities per 100,000 population. Control variables include: population, population density, share of population with a high school diploma, share of population with a college degree, median household income, share of population who are white, share of population who are Black, share of population who are Asian, share of population who are Hispanic, share of population who are male, CBSA GDP, share of fatal crashes that involved alcohol, and average age of drivers involved in fatal crashes.

substituted with cars. Across 2000-2018 I estimate that 8,029 pedestrian lives would have been saved if all light trucks had been cars. The reduction would be equal to avoiding 9.9% of all pedestrian deaths. In 2000, converting all light trucks to cars would have spared 375 pedestrians, while by 2018 the figure had grown by 23% to 463 pedestrians. However, accounting for the overall population increase of the metros, the number of pedestrian deaths attributable to light trucks increased by only 4.4% on a per capita basis.

I find an increasing impact of SUVs, particularly Large SUVs, on pedestrian

Figure 4: Annual Pedestrian Deaths Averted if all Light Trucks had been Cars



Relying on estimated partial effects, the figure plots the number of pedestrian fatalities that would have been averted if all light trucks were replaced by cars. Over the entire study period, converting all light trucks to cars would have prevented 8,029 pedestrian deaths.

fatalities. In 2000, if all SUVs were substituted with cars, there would have been 96 fewer pedestrian fatalities across all metros. By 2018, the substitution of SUVs for cars would have averted 206 pedestrian fatalities. The change represents a 115% increase or 81% on a per capita basis. Figure 4 breaks out the effect of Large and Small SUVs. While Large SUVs are much less common than Small SUVs, their marginal effect on pedestrian safety is much larger. The 131% increase in Large SUVs as a share of the vehicle fleet over the study period led to large negative effects on pedestrian safety. Across all years in the sample period I estimate that replacing all SUVs with cars would have averted 3,048 pedestrian deaths, with 1,600 of these deaths attributable to Large SUVs. Maintaining the shares of Small and Large SUVs across the study period at 2000 levels and replacing that growth with cars would have averted 1,128 pedestrian fatalities.

Figure 4 shows how the categories of light trucks changed in their contribution to pedestrian deaths over the study period. The sharp increase in SUVs as a share of metropolitan consumer vehicles (12.9% to 23.2%) caused a significant increase in pedestrian deaths. However, over this period the share of pickups and minivans both fell. Pickups as a share of vehicles fell from 15.4% to 13.9% and minivans fell from 10.4% to 6.0%. I estimated in Table 3 that both pickups and minivans have a significantly harmful effect on pedestrian safety relative to cars. The decline in pickups and minivans worked to counteract the negative pedestrian safety effects of increased SUVs.

An interesting policy question is what would have happened if the class of Large SUVs, which were rare on US roads prior to 2000, had instead had the characteristics of Small SUVs. This counterfactual may relate to a world in which US regulators limited the sizes of SUVs. Again, using the partial effects estimated in Table 3, I estimate that if all Large SUVs were replaced with Small SUVs, 1,121 pedestrian deaths would have been averted, including 80 deaths in 2018 alone.

As noted in the introduction, there was a substantial increase in pedestrian fatalities during the 2000-2018 period. Between 2000 and 2018 the pedestrian fatality rate across all metro areas increased by 15%, from 1.72 to 1.98 deaths per 100,000 residents. The overall rise in light trucks over this period was modest, as the rise in SUVs was buffered by the decline in pickups and minivans. Table 4, column 3 estimates imply that if the prevalence of all light truck categories had remained at the 2000 level across the study period there would have been 377 fewer pedestrian deaths between 2000 and 2018, including 30 fewer in 2018. Rather than being 1.98 deaths per 100,000 in 2018, the pedestrian fatality rate would have been 1.97 if light truck shares had remained at 2000 levels. The result suggests that a shift in the vehicle fleet is not responsible for the overall increase in pedestrian deaths. However, converting all Large SUVs to Small SUVs would have reduced the 2018 rate to 1.95 and converting all light trucks to cars would have reduced the rate to 1.81.

The above estimates ignore incidents occurring outside of metropolitan areas. Metropolitan areas contained 77% of the US population across the study period. To the extent that non metropolitan areas are experiencing negative pedestrian safety effects from larger vehicles, the estimates understate the national effect. However, the effects in less urbanized areas may be markedly different.

A commonly noted motivation for purchasing a large vehicle is the presumed increase in driver and passenger safety. Potentially, the above estimated increases in pedestrian fatalities have been offset by an improvement in motorist safety. I repeat the panel regression specifications (Equations 1 and 2), but rather than estimate the effect on pedestrians I estimate the effect of vehicle characteristics on the traffic fatality rate among drivers and their passengers (Table 6).[6] Overall, I find no evidence of a relationship between the change in vehicle characteristics and changes in motorist fatalities across metros. None of the light truck categories appear statistically significant, which suggests that shifting fleet shares have not contributed to improved motorist safety. The statistically insignificant effect of large vehicles on motorist fatalities can be attributed to the mechanism proposed in prior literature wherein the safety benefits imparted to the occupants of large vehicles are counteracted by the negative safety impacts on other motorists. While statistically insignificant, the coefficient estimated for the effect of Large SUVs on motorist fatalities is large, suggesting that Large SUVs may reduce motorist safety in aggregate. The column 5 estimate suggests that a 10 percentage point shift from cars to Large SUVs would increase motorist fatalities by .20 deaths per 100,000 residents annually, equal to a 1.6% increase in a metro with the median motorist fatality rate.

The share of motorcycles appears to have a large negative effect on the rate of motorist fatalities. The result is mainly an artifact of motorcycles rarely having passengers. The average motorcycle involved in a fatal crash carried 1.14 people, while the average car carried 1.60, the average light truck carried 1.70 and the average SUV carried 1.80. In the counterfactual where cars are replaced with motorcycles, the implication is there would be fewer people on the road generally, which would lower fatalities mechanically. Motorcycles also have a limited ability to harm the occupants of other vehicles due to their small size. For interpreting coefficients in the motorist regression results (Table 6), it is possible that larger vehicles may lead to more fatalities simply because they can accommodate more passengers. Therefore, coefficient estimates for larger vehicles may be biased upwards slightly. Notably, this source of bias is not relevant to the pedestrian findings.

The insignificant effect of light trucks on motorist fatalities contrasted with the highly significant results of the pedestrian fatality regressions provide additional support to the validity of the main estimation strategy. If the meaningful variation was related to omitted variables regarding general changes in road safety I would expect the motorist regressions to also indicate significant effects.

[6] I estimated the same regression on the cyclist fatality rate but found no statistically significant coefficients. Cyclist fatalities are rare relative to motorist or pedestrian fatalities, causing imprecision in estimates.

Table 6: Effect of Vehicle Characteristics on Vehicle Occupant Fatality Rate

	(1)	(2)	(3)	(4)	(5)
Weight (100 kg)	-0.107				-0.109
	(0.063)				(0.095)
Light truck share		-0.745			
		(0.508)			
SUV share			-0.067		
			(0.661)		
Small SUV share				-0.391	-0.083
				(0.703)	(0.774)
Large SUV share				1.046	1.953
				(1.120)	(1.439)
Pickup share			-1.364	-1.370	-0.565
			(0.764)	(0.764)	(1.063)
Minivan share			-0.649	-0.639	-0.158
			(0.883)	(0.884)	(0.953)
Motorcycle share		-7.406**	-7.355**	-7.344**	-6.517**
		(2.138)	(2.128)	(2.129)	(2.134)
CBSA fixed effects?	Y	Y	Y	Y	Y
Year fixed effects?	Y	Y	Y	Y	Y
Control variables?	Y	Y	Y	Y	Y
R^2	0.327	0.328	0.328	0.328	0.329
N	6878	6878	6878	6878	6878

Significance levels: $*$: 5% $**$: 1%. Standard errors are shown in parenthesis and are clustered at the CBSA level. The dependent variable is the number of driver and passenger fatalities per 100,000 population. Control variables include: population, population density, share of population with a high school diploma, share of population with a college degree, median household income, share of population who are white, share of population who are Black, share of population who are Asian, share of population who are Hispanic, share of population who are male, CBSA GDP, share of fatal crashes that involved alcohol, and average age of drivers involved in fatal crashes.

5 Conclusion

I estimate that the popularity of light trucks on US roads is responsible for a large number of pedestrian deaths. If all light trucks were replaced with cars, over 8,000 pedestrian deaths would have been averted between 2000 and 2018. Vehicle body types appear to be an important determinant of pedestrian deaths in the aggregate, strengthening arguments made in the transportation safety literature regarding the link between larger light trucks and more severe pedestrian injuries.

Average vehicle size has undergone a sustained increase over the past 20 years, with no signs of abating. If the popularity of large vehicles continues to rise there is likely to be a corresponding increase in pedestrian fatalities. Given strict federal regulation of vehicle safety standards, it is perhaps surprising that there is limited legislation that restricts the overall size and body type of vehicles with the intent of improving pedestrian safety. It is unlikely that the purchase decision of car owners will take account of the safety externalities that large vehicle body types impose on pedestrians (Lindberg, 2005). These facts suggest there could be societal benefits from restricting sales of large vehicles, or implementing a Pigouvian tax on particular vehicles, as was suggested in Anderson (2008), Anderson and Auffhammer (2014) and Li (2012).

A single consumer's decision to substitute a car for a light truck raises the predicted number of pedestrian deaths marginally. I calculate the marginal external cost of a consumer switching from a car to a light truck. To calculate marginal external costs I use the US Department of Transportation's value of a statistical life ($10.45 million in 2020 USD), main regression estimates (Table 3, column 4) and the fact that there were 46.0 registered vehicles in the US for every 100 residents according to the FHWA 2018 data. The marginal external cost of switching from a car to a Large SUV in terms of added pedestrian deaths is $173 annually. The annual cost associated with switching from a car to a Small SUV, pickup truck or minivan is $52, $115 and $116 respectively. Optimal Pigouvian taxes that internalize the external costs of pedestrian fatalities attributable to driving a light truck over a car could be implemented with annual taxes by vehicle types that are equal to these marginal external costs. These taxes would be in addition to other taxes that may address other externalizes of vehicles. Assuming a 10 year vehicle lifespan suggests that if the tax were applied at the time of sale, the one time tax would need to be roughly 10 times the rates calculated above. For example, Large SUVs would be assessed a point of sale tax equal to $1,730 in order to internalize the pedestrian fatality risk.

Using the value of a statistical life, the implied economic cost of the 8,029 pedestrian deaths attributable to the presence of light trucks between 2000 and 2018 is $84 billion. The possibility of reducing the pedestrian safety externalities imposed by large vehicles through regulation could provide significant societal welfare improvements.

The shift in vehicle types over the study period is unable to account for the dramatic rise in overall pedestrian deaths. While the increased popularity of SUVs caused a significant number of deaths, the declining popularity of pickup trucks and minivans offset the majority of this trend. Other changes to vehicles and road conditions over this period are deserving of future study and may be able to account for the rise in aggregate pedestrian deaths. In particular, the rapid shift in personal consumer technologies may have impacted road safety during the same period. The proliferation of smartphones among both drivers and pedestrians presented a new distraction for road users (Lin and Huang, 2017; Ortiz et al., 2018; Vollrath et al., 2016). Additionally, the decision of automakers to include complex navigation and entertainment consoles in vehicles may have served to reduce drivers' ability to monitor for pedestrians.

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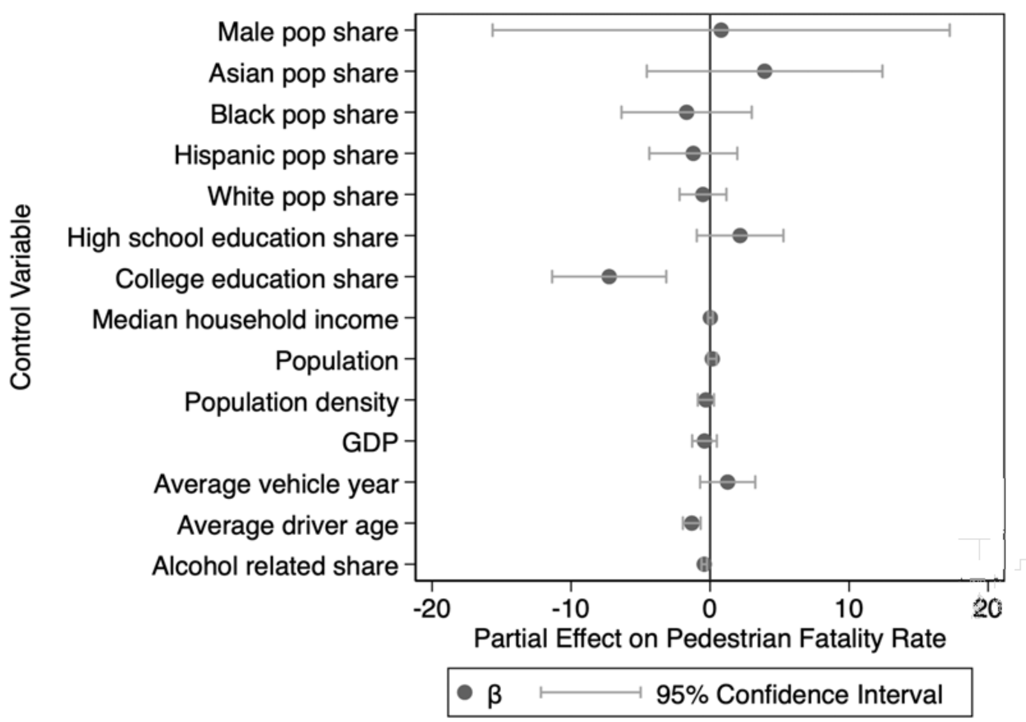
Appendix A

In the main tables I omit the partial effects of control variables to focus on the effects of vehicle fleet characteristics. Figure A1 provides information on the estimated coefficients of control variables. I show results that correspond to the estimates from Table 3, column 4. The estimated partial effects of control variables are very similar across all specifications in Table 3.

A1. Control Variable Coefficient Estimates



Coefficient estimates for control variables from the main model specification are shown. I convert the units of some variables to improve the readability of the chart. All "shares" range from 0-1. Median household income is in \$10,000s, population is in millions, population density is in 100 persons per km^2, GDP is in billions and average vehicle year and age are in 100s of years.

I find three control variables have a statistically significant effect on the pedestrian fatality rate; average driver age, the local college education rate and alcohol related incidents. An increase in the average age of drivers involved in fatal crashes within a metro is correlated with fewer pedestrian fatalities. The negative correlation potentially suggests that driver experience improves the safety of pedestrians (Deery, 1999). An increase in a metro's college education rate is strongly correlated with a lower pedestrian fatality rate, suggesting education is correlated with road safety. The share of the population with a high school education does not appear as significant.

The share of fatal crashes that involved alcohol is correlated with *fewer* pedestrian fatalities. This at first seems counterintuitive; however, a rise in the share of incidents involving alcohol could be caused by increased drunk driving, or equally by a decline in incidents among sober drivers. 41% of crashes that cause a motorist death involve alcohol, but only 25% of crashes that involve a pedestrian death involve alcohol. Therefore, a rise in the share of incidents involving alcohol is correlated with fewer pedestrian deaths but more motorist deaths. I find the drunk driving control variable is significant and positively related to motorist deaths in the Table 6 regressions.

Despite some control variables being statistically significant, their inclusion does not significantly affect the main results of the paper. Table A1 repeats the main regressions of the paper but omits all metro-year control variables. Comparing the results to those of Table 3 demonstrates that estimates are insensitive to the inclusion of metro-year level control variables.

Table A1. Effect of Vehicle Characteristics on Pedestrian Fatality Rate, No Control Variables

	(1)	(2)	(3)	(4)	(5)
Vehicle weight (100 kg)	0.037*				0.006
	(0.015)				(0.019)
Light truck share		0.473**			
		(0.128)			
SUV share			0.337*		
			(0.162)		
Small SUV share				0.194	0.176
				(0.185)	(0.185)
Big SUV share				0.836**	0.785*
				(0.311)	(0.344)
Pickup share			0.444*	0.443*	0.397
			(0.178)	(0.179)	(0.215)
Minivan share			0.467*	0.472*	0.445
			(0.223)	(0.223)	(0.244)
Motorcycle share		-2.352**	-2.458**	-2.446**	-2.494**
		(0.575)	(0.579)	(0.580)	(0.601)
CBSA fixed effects?	Y	Y	Y	Y	Y
Year fixed effects?	Y	Y	Y	Y	Y
Control variables?	N	N	N	N	N
R^2	0.042	0.049	0.048	0.049	0.049
N	6878	6878	6878	6878	6878

Significance levels: $*$: 5% $**$: 1%. Standard errors are shown in parenthesis and are clustered at the CBSA level. The dependent variable is the number of pedestrian fatalities per 100,000 population.

Appendix B

I apply a conventional difference in difference regression design as the main model in the above analysis. In Table B1 I repeat the main analysis but add controls for metro specific linear time trends. The models estimated are identical to Equations 1 and 2, with the addition of a vector of metro level linear time trends.

Table B1. Effect of Vehicle Characteristics on Pedestrian Fatality Rate, Linear Metro Time Trends

	(1)	(2)	(3)	(4)	(5)
Vehicle weight (100 kg)	0.029				-0.017
	(0.015)				(0.020)
Light truck share		0.503**			
		(0.134)			
SUV share			0.336		
			(0.175)		
Small SUV share				0.236	0.286
				(0.200)	(0.201)
Big SUV share				0.679*	0.824*
				(0.323)	(0.352)
Pickup share			0.538**	0.535**	0.665**
			(0.186)	(0.186)	(0.235)
Minivan share			0.582*	0.584*	0.662**
			(0.229)	(0.230)	(0.255)
Motorcycle share		-1.842**	-1.912**	-1.906**	-1.768**
		(0.613)	(0.616)	(0.616)	(0.644)
CBSA fixed effects?	Y	Y	Y	Y	Y
Year fixed effects?	Y	Y	Y	Y	Y
CBSA time trends?	Y	Y	Y	Y	Y
Control variables?	Y	Y	Y	Y	Y
R^2	0.122	0.127	0.127	0.127	0.127
N	6878	6878	6878	6878	6878

Significance levels: $*$: 5% $**$: 1%. Standard errors are shown in parenthesis and are clustered at the CBSA level. The dependent variable is the number of pedestrian fatalities per 100,000 population.

I find results are robust to the inclusion of metro time trends, with point estimates and standard errors changing very little between Tables 3 and B1. The estimate of vehicle weight's impact on pedestrian fatalities falls short of statistical significance when time trends are added (column 1), providing more evidence that weight is relatively less important than vehicle body type.