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Fuel Economy and Safety: The Influences of Vehicle Class and Driver Behavior†

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Fuel economy standards change the composition of the vehicle fleet, influencing accident safety. The direction and size of the effect depend on the combination of vehicles in the fleet. I provide empirical estimates of vehicle safety across classes, accounting for unobserved driving behavior and selection. I apply the model to the present structure of US fuel economy standards, accounting for shifts in the composition of vehicle ownership, and estimate an adverse safety effect of 33 cents per gallon of gasoline saved. I show how two alternative regulatory provisions fully offset this effect, producing a near-zero change in accident fatalities. (*JEL* D12, L51, L62, Q48, R41)

Policy to reduce gasoline use in the United States changes the composition of the vehicle fleet and so influences accident safety. I estimate the effect of different vehicle classes on total fatalities per mile driven, measuring risks to occupants of each class and to those around them in the rest of the fleet. I use the estimates to consider the safety impacts of three alternative forms of the US fuel economy standard. My findings build on a literature investigating the overall welfare cost of fuel economy standards and gasoline taxes (Goldberg 1998; Portney et al. 2003; Austin and Dinan 2005; Bento et al. 2009; Anderson and Sallee 2011; Busse, Knittel, and Zettelmeyer 2013; Klier and Linn forthcoming).

Countervailing effects in the fleet mean both the direction and magnitude of the effect of fuel economy rules on safety are empirical questions. For example, if the number of large cars is reduced the frequency of unevenly matched, dangerous accidents between large and small cars will decline. However, protective effects offered by the larger vehicles will also be lost. The high cost of traffic accidents in the United States means that small increases or decreases in overall risk importantly alter the cost of gasoline policy.[1]

I first estimate the effect of each of ten vehicle classes—defined to span all vehicles in the fleet—on safety. These estimates are a 10×10 matrix that flexibly captures

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[1] There were 37,261 US traffic fatalities and more than 2.3 million injured in 2008. (National Highway Traffic Safety Administration (NHTSA) 2009).

the fatality risk from each combination of classes. It measures risks to drivers inside each class, and also the risks imposed on every other class.[2] Risk is evaluated per mile that the two vehicles each are driven (and so are interacting on the road). The novel structure of my estimates allows me to consider arbitrary changes in the fleet, reevaluating overall fatality risk as the distance driven in each class changes. I will also be able to control for unobserved risk associated with drivers who select into each class. These driver-related effects can be reallocated in counterfactual fleets.

I apply the estimated model to three variations of US fuel economy policy: the corporate average fuel economy (CAFE) rules in place since 1978, a unified average standard, and "footprint"-based regulation in place for model years 2012 to 2016.[3] Each policy creates different incentives on fleet composition and correspondingly disparate effects on safety. The results have important implications for the cost of improvements in fuel economy mandated through 2016, as well as for the even more ambitious target announced for 2025 of nearly doubling fuel economy relative to today's fleet.[4]

I estimate the fleet-wide impact of historical CAFE rules to be 149 additional annual fatalities per mile-per-gallon (MPG) increment in stringency. In this case, the shift to smaller vehicles within the car and light truck categories prescribed under CAFE causes deterioration in safety that is only partially offset by reductions in poorly matched accidents. The safety effect translates to a welfare cost of approximately 33 cents per gallon of gasoline saved.[5] In the context of related environmental externalities, damages of \$25 per ton CO_2 amount to 22 cents per gallon of gasoline, and Parry and Small (2005) report costs from local air pollution of about 16 cents per gallon.

I next consider a unified fuel economy policy that combines size reductions within the car and truck categories with broader switching between the two categories. Holding the improvement in fuel economy constant, I find this policy results in an increase of only eight fatalities per year with a zero change included in the confidence band. The dramatically reduced cost relative to the CAFE rules comes via two offsetting effects within the fleet. Finally I consider a "footprint" type rule and show that it, too has a near-zero effect on fatalities. The mechanism for the neutral safety outcome under a footprint rule is quite different than the case of the unified standard, and is likely to raise policy cost along other dimensions.

The empirical model I develop here fits into a longer literature on vehicle safety and offers two key methodological advantages. First, my semiparametric approach

[2] My estimates therefore distinguish between internal and external costs if we can assign changes in the protective effect across cars as internal and changes in damage to other vehicles as external. However, health, life, and disability insurance (not conditioned on vehicle choice) make part of the protective effect external, while automobile liability insurance, psychic costs, and the potential for civil and criminal liability internalize part of the risk a vehicle imposes on others. I therefore focus on total accident cost in the fleet when comparing policy counterfactuals.

[3] Khazzoom (1994), Noland (2004), and Ahmad and Greene (2005) investigate time-series changes in safety around the 1978 introduction of fuel economy rules.

[4] National Highway Traffic Safety Administration and Environmental Protection Agency (2010), and The White House Office of the Press Secretary (2011).

[5] To the extent much of vehicle safety is external this cost is not captured in earlier estimates. Jacobsen (forthcoming) and Anderson and Sallee (2011), for example, estimate efficiency costs of CAFE to be less than \$2.00 per gallon.

nests earlier studies of individual vehicle attributes in isolation.[6] Because I separately identify the effect of each class on every other, any characteristic (or combination of characteristics) differing by class is implicitly included. I will show how my estimates continue to reflect the protective and external effects of weight measured in earlier studies.[7] At the same time, I flexibly capture the risks that pickup truck and SUV classes (independent of weight) impose on other vehicle types. This brings a separate strand of the literature into a single framework, allowing me to measure the relative importance of competing effects.[8]

The second key feature of my model comes in accounting for unobservable driver attributes: riskier drivers may cluster in certain classes, biasing measures of how dangerous those vehicle models really are.[9] I combine information on single- and multiple-vehicle accidents with results from crash tests to identify driver-related risk. When certain classes have an excess of single-car fatalities, I will link this to a greater probability of fatal two-car accidents. Identification comes from relative risk in different classes within bins of the data grouped by location and time of day. The results allow me to address, for example, a puzzle in the literature concerning minivans. My model attributes their scarcity in fatal accidents largely to unobserved driver behavior rather than to the vehicles themselves. More generally, I find that accounting for driver-related risk significantly alters estimates of safety by vehicle class and is pivotal in the analysis of CAFE policy.

The rest of the paper is organized as follows. Section I describes a model of fleet safety across vehicle classes and accident types. Sections II and III describe the data and present results from estimation. Sections IV and V describe the policy experiments and present a variety of alternative specifications. Section VI concludes.

I. Model of Accident Counts

I model the count of fatal accidents in each vehicle class, measured per billion miles traveled. Vehicle classes will be a set of $\mathcal{J}$ categories covering the entire vehicle fleet; the physical characteristics of each vehicle class are interesting in policy examples but do not enter the general model specification.

Define F_{ij} as the count of fatal accidents where vehicles of class i and j have collided and a fatality occurs in the vehicle of class i. The counts will be asymmetric, that is $F_{ij} \neq F_{ji}$, to the degree that some classes impose greater risks on others. If a fatality occurs in both vehicles in an accident, then F_{ij} and F_{ji} are both incremented, though this will be relatively rare in the data.

[6] Kahane (2003) summarizes findings that combinations of weight, height, frame rigidity, and wheelbase may all be important determinants of own and others' safety.

[7] Crandall and Graham (1989) find very strong protective effects of vehicle weight, suggesting adverse effects of CAFE. Recent work by Anderson and Auffhammer (2011) instead focuses on the increased risks that weight imposes on other vehicles, demonstrating how they may be reduced using gasoline or weight-based taxes.

[8] White (2004), Gayer (2004), Anderson (2008), and Li (2012) present results on the external safety cost of light trucks.

[9] A number of other approaches to this problem appear in the literature: fatality risk can be measured conditional on an accident occurring (Anderson and Auffhammer 2011), or using fault measures, where innocent vehicles would be selected at random (Levitt and Porter 2001).

The total count of fatal accidents in class i vehicles is then

$$(1) \qquad (\text{fatalities in class } i) = \sum_{j \in \mathcal{J}} F_{ij}.$$

By changing the order of subscripts we can similarly write the count of fatalities that are imposed on other vehicles by vehicles of class i:

$$(2) \qquad (\text{fatalities imposed on others by class } i) = \sum_{j \in \mathcal{J}} F_{ji}.$$

The count of fatal accidents reflects a combination of factors influencing risk and exposure. I divide these into three multiplicative components: (i) The risk associated with drivers in each vehicle class, (ii) risk coming from physical vehicle characteristics—I will term this the "engineering" risk, and (iii) the miles driven in each class. Intuitively, the greater driver recklessness or location risk, engineering risk, or miles driven, the more fatal accidents we should expect to see of type F_{ij}.

Define the three components using:

- α_i The riskiness of drivers selecting each vehicle class i (in estimation this will appear as a fixed effect on driver behavior for each class; in counterfactual simulations it will be allowed to vary as drivers switch across classes).

- β_{ij} The risk per mile of a fatality in vehicle i when vehicles from class i and class j are driven by average drivers (β_{ij} will be estimated for all possible combinations of vehicles).

- m_i The number of miles driven in vehicles of class i (available as data below).

I normalize the measure of driver riskiness, α_i, to unity for the average driver so that it functions as an accelerator multiplying the overall risk per mile driven. For example, a value of $\alpha_i = 2$ corresponds to a driver who generates twice the average fatality risk for each mile they drive. High values of α_i come from a tendency of class i owners to live in locations with dangerous roads, travel at high risk times of day, drive recklessly, distracted or drunk, or have other characteristics (observable or unobservable) that increase risk per mile of fatal accidents. This means α_i can operate either through an increase in the number of collisions or through an increase in fatality risk after a collision has occurred; the distinction is not needed to consider total fatalities in the fleet.

I model the probability of a fatal accident in class i (when interacting on the road with class j) as the product of underlying engineering risk, β_{ij}, and the parameters representing high risk coming from the drivers involved, α_i and α_j:

$$(3) \qquad \text{Probability of a fatal accident in vehicle } i \,|\, i, j \text{ driven 1 mile} = \alpha_i \alpha_j \beta_{ij}.$$

The multiplicative form contains an important implicit restriction—behaviors that increase risk are assumed to have the same influence in the presence of different classes and driver types. I argue that this is a reasonable approximation given that most fatal accidents result from inattention, drunk driving, and signal violations (NHTSA 2008). Such accidents give drivers little time to alter behavior based on attributes of the other vehicle or driver.

I next include the effect of the number of miles traveled in each class, m_i, and further subdivide miles and fatalities into bins s based on time and location. If pickup trucks are less common on urban roads, or minivans tend to be parked at night, there should be differences in the number of accidents involving these vehicles across time and space. In the estimation below I define 18 bins according to time of day, average local income, and urban density—factors that appear to significantly influence both the composition of the fleet and the probability of fatal accidents.

The effect of miles driven in bin s on the number of fatalities again takes a natural multiplicative form. If twice as many miles are driven in a certain class then we expect twice as many cars of that class to be involved in an accident:

$$E(F_{ijs}) = m_{is} m_{js} \alpha_{is} \alpha_{js} \beta_{ij}. \tag{4}$$

I also place a bin s subscript on α since the risk multiplier may differ across time and space. Broadly speaking, data will be available on F and m leaving α and β to be estimated. I will not observe m_{is} at the bin level, but show below how the average of α_{is} in each class, α_i, can still be recovered empirically.

The key challenge in this literature becomes clear in equation (4). Since the α terms include unobservable driving behavior, and the engineering risks β are also to be estimated, we need a way to separate the two. Is a vehicle class dangerous because of its engineering characteristics, or do the drivers who select that class just happen to have high risk (from factors like the location where they live or poor driving habits)?

I will identify driver risk via a second equation describing single-car fatalities, using the assumption that overall driver risk (in α_{is}) influences both equations. I define the count of fatal single-car accidents in vehicle class i as F_{i0}, where

$$E(F_{i0s}) = m_{is} \alpha_{is} \lambda_s h_i. \tag{5}$$

The four components are:

m_{is} (As above) The number of miles driven in class i and bin s.

α_{is} (As above) The riskiness of drivers or the locations they live in.

λ_s Controls the relative frequency of fatal single-car accidents separately for each bin.

h_i The relative fatality risk to occupants of class i in a standardized collision (measured using crash test data, or in an alternative specification through additional restrictions on β_{ij}).

The key identifying restriction across equations (4) and (5) is that dangerous locations or behaviors (in α) that differ across classes enter both the risk of single-car accidents and the risk of accidents with other vehicles. This may be a better assumption for some factors (geographical location, drunk driving, recklessness) than others (falling asleep), but I will argue below that the estimates closely match intuition on driver safety. Further, λ_s allows flexibility in the relative frequency of single- and two-car accidents (for example single car accidents are more frequent at night) and importantly relaxes the stringency of the identifying restrictions; Section III provides more intuition on the nature of the restriction and role of λ_s in the context of my data.

A. *Comparison with Other Models of Safety*

Much of the work focusing on the influence of vehicle characteristics on safety (see Kahane 2003) has taken a parametric approach in an attempt to isolate the effect of weight alone. By separately modeling risk in each possible interaction, β_{ij}, I add considerable flexibility. The cost to my approach comes in the degree of aggregation. I will consider 10 distinct classes, for 100 separate β_{ij} parameters. Since each class contains a variety of vehicles I must assume that changes caused by regulation inside a class are of relatively small importance compared with the changes across classes. The assumption will have the most influence at the extremes of the distribution, for example downsizing within the compact class and within the large pickup class. In the context of safety, these biases will cancel out to some degree, though this remains an important caveat.

Wenzel and Ross (2005) describe overall risks using a similarly flexible class-based approach, but do not model driving safety behavior and so are unable to separate it from underlying engineering risk. For purpose of comparison, I provide estimation results from a restricted version of my model, where I set all the α_{is} terms equal. The parameter estimates turn out to be quite different, so much so that the primary economic and policy implications are reversed in sign.

II. Data

I assemble data on each of the three variables needed to identify the effects in equations (4) and (5): counts of fatal accidents as F_{ij} and F_{i0}, the number of miles driven in each class as m_i, and crash test data to describe risks in single-car accidents as h_i.

A. *Fatal Accident Counts*

I incorporate data from the Fatality Analysis Reporting System (FARS), which records each fatal automobile accident in the United States. The dataset is complete and of high quality, due in part to the importance of accurate reporting of fatal accidents for use in legal proceedings. If such complete data were available for accidents involving injuries or damage to vehicles it could be used in a framework similar to the one I propose, but reporting bias and a lack of redundancy checking in police reports for minor accidents make those data less reliable.

The FARS data include information about vehicle class and where and when the accident took place, as well as a host of other factors like weather and driver characteristics. While the additional data is not needed in my main specification, I will make use of a number of these other values to consider robustness in subsamples.

I define the bins s using three times of day (day, evening, night), two levels of urban density, and three levels of income in the area of the accident. For the latter two items I use census data on the zip codes where the accidents take place. This creates 18 bins in my central specification that, together with weekly variation, produce the replicates on F_{ij} used for estimation. The key parameters of interest are at the vehicle class level, rather than bin level, and the selection of bin divisions turns out to have a relatively small impact empirically. I explore both more and less aggregate bin structures in the online Appendix.

For my main specification I pool fatal accident counts for the years 2006 to 2008. I experiment with month of sample fixed effects and a nonoverlapping sample of data from 1999 to 2001 and find no important differences in results. The selection of the time period is to match the timing of data on vehicle quantities and miles driven (see below), observed in 2001 and again in 2008. The pooled sample provides additional power in estimation.

B. *Miles Driven*

Data on vehicle miles traveled (VMT) in each class, m_i, is available from the 2009 National Household Transportation Survey (NHTS). The data cover more than 150,000 US households surveyed in 2008 and can be directly matched with the FARS using NHTSA make and model codes. While I do have some information about the location of VMT (for example the home state of the driver), I do not observe other important aspects like the time of day or type of road. As shown in Section III, it is still possible to recover the parameters defining driver behavior using only total VMT for each class. Differences in bin s level VMT are absorbed in fixed effects.

While the NHTS enjoys wide use it remains subject to a number of caveats. In my application sampling or reporting bias correlated with driver risk is a main concern. Fortunately, many of the characteristics used in constructing the sample weights for the NHTS are also associated with safety (e.g., age, income, and, of particular relevance here, geographical location). Sampling bias at the level of individual models or localities is of less concern in my application to the extent it is uncorrelated with class-level VMT.

C. *Crash Test Data*

NHTSA has performed safety tests using crash-test dummies since the 1970s, with recent tests involving thousands of sensors and computer aided models to determine the extent of life-threatening injuries likely to be received. The head injury criterion (HIC) is a summary index reflecting the probability of a fatality very close to proportionally (Herman 2007), and appears in my model as h_i. This accords well with the multiplicative risk appearing in equation (5).

Table 1—Summary Statistics by Class

Class	Count of accident fatalities[a]		Total miles driven[b]	Single vehicle fatality rate[c]	Crash test HIC[d]
	Own vehicle	Other vehicle			
Compact	2,812	1,068	247.7	14.3	528.7
Midsize	2,155	1,280	249.7	11.3	491.4
Fullsize	733	507	83.2	10.2	353.9
Small luxury	317	236	54.5	13.5	424.3
Large luxury	364	307	50.8	11.9	469.3
Small SUV	719	1,129	216.0	9.4	626.3
Large SUV	477	1,379	148.9	12.8	531.2
Small pickup	594	624	87.1	15.9	666.2
Large pickup	716	2,293	159.5	18.2	585.9
Minivan	469	532	126.7	4.9	577.9

[a] Two-vehicle accidents, annual average 2006–2008.
[b] In billions of miles per year (2008 NHTS).
[c] Fatal single car accidents per billion miles traveled, annual average 2006–2008.
[d] Results from NHTSA testing 1992–2008. The head-injury criterion (HIC) score has been shown to be closely and linearly related to fatality rates. Controlling for driver behavior, a doubling in the score should correspond to a doubling of fatality rates.

I assemble the average HIC by vehicle class for high-speed frontal crash tests conducted by NHTSA over the period 1992 to 2008.[10] The tests are meant to simulate typical collisions with fixed objects (such as concrete barriers, posts, guardrails, and trees) that are common in many fatal single-car accidents. These data suggest single-vehicle accidents in small pickup trucks, the most dangerous class, are nearly twice as likely to result in a fatality as those occurring in large sedans, the safest class, all else equal.

The crash test data is more difficult to defend than my other sources since it relies on the ability of laboratory tests to reproduce typical crashes and measure injury risks. I therefore offer an alternative specification in Section V that abstracts altogether from crash-test data. It produces similar results though they will not be as precise.

D. *Summary Statistics*

I define ten vehicle classes spanning the US passenger fleet, including various sizes of cars, trucks, SUVs, and minivans. Table 1 provides a list and summarizes fatal accident counts in the first two columns, reflecting fatalities in each class and in opposing vehicles. Column 3 summarizes annual VMT data and column 4 presents single-vehicle fatality rates per billion VMT. The final column displays the HIC data for each class. The contrast between risks measured in the HIC and actual fatality rates per mile highlights the importance of controlling for selection on driver location and behavior.

Table 2 summarizes the data on fatal accidents divided according to bin s. The first three columns contain total fatal accidents in my sample, counting only one- and two-car accidents. Column 4 shows variance at the weekly level as used in estimation. Columns 5 and 6, respectively, display the fraction of accidents that involve

[10] Specifically, I include all NHTSA frontal crash tests involving fixed barriers and a test speed of at least 50 miles per hour. This filter includes the results from 945 tests.

Table 2—Summary Statistics by Bin s

	Fatalities (one- and two-car accidents)						Greatest relative frequency[b]	
Bin (density, income, time of day)[a]	2006	2007	2008	Variance (weekly)	Fraction one-car	Fraction light trucks	One-car accidents	Two-car accidents
Rural, low, night	705	673	582	3.92	0.882	0.557	Lg pickup	Fullsize/Fullsize
Rural, low, evening	374	373	320	2.77	0.718	0.485	Lg pickup	Fullsize/Fullsize
Rural, low, day	1,574	1,475	1,310	6.66	0.643	0.519	Lg pickup	Sm pickup/Lg pickup
Rural, medium, night	501	518	414	3.47	0.883	0.537	Lg pickup	Compact/Lg lux
Rural, medium, evening	254	257	210	2.16	0.756	0.535	Sm pickup	Fullsize/Fullsize
Rural, medium, day	1,022	1,003	897	4.97	0.585	0.498	Sm pickup	Sm pickup/Lg pickup
Rural, high, night	341	308	266	2.71	0.897	0.460	Lg pickup	Sm lux/Sm pickup
Rural, high, evening	150	133	144	1.65	0.728	0.478	Sm pickup	Lg lux/Lg lux
Rural, high, day	639	645	540	4.02	0.550	0.459	Lg pickup	Compact/Lg pickup
Urban, low, night	587	570	532	3.53	0.827	0.528	Lg pickup	Compact/Lg Pickup
Urban, low, evening	283	265	222	2.37	0.655	0.491	Lg pickup	Sm lux/Sm lux
Urban, low, day	1,133	1,062	953	4.91	0.609	0.528	Lg pickup	Sm pickup/Lg pickup
Urban, medium, night	1,038	995	946	4.83	0.822	0.491	Lg pickup	Lg lux/Lg lux
Urban, medium, evening	478	437	368	2.95	0.652	0.471	Lg pickup	Lg lux/Lg pickup
Urban, medium, day	1,850	1,671	1,569	6.72	0.571	0.473	Lg pickup	Compact/Lg pickup
Urban, high, night	4,234	4,085	3,565	11.96	0.766	0.380	Sm lux	Compact/Sm lux
Urban, high, evening	1,490	1,404	1,229	5.96	0.599	0.385	Sm lux	Compact/Lg pickup
Urban, high, day	5,786	5,525	4,801	14.16	0.511	0.386	Compact	Compact/Lg pickup
All	22,439	21,399	18,868	41.85	0.650	0.441	Lg pickup	Compact/Lg pickup

[a] Based on zip-code level classifications from the US Census.

[b] Relative frequencies are calculated as accident counts within group divided by total miles traveled. A combination of vehicle popularity and driver behavior within group determines the accident with greatest relative frequency.

one car and where the fatality is in a light truck. More than half of fatal accidents involve only one car. Finally, the last two columns show the accident types with the highest relative frequency. Pickups are involved in the most single-car accidents per mile everywhere except in the highest income cities. Two-car accidents are more varied, with luxury vehicles involved in the evening and at night, and compacts much more likely to have a fatality (the vehicle with the fatality is listed first). A summary of accident rates per mile across all 100 possible combinations of classes appears below in Table 3.

III. Estimation

I now describe estimation of the model outlined in Section I. F_{ijs}, F_{i0s}, m_i, and h_i will be data as above and α_i, β_{ij}, and λ_s are estimated. The equations representing single- and multi-car accidents are

$$(6) \qquad E(F_{i0s}) = m_{is}\alpha_{is}\lambda_s h_i$$

$$E(F_{ijs}) = m_{is}m_{js}\alpha_{is}\alpha_{js}\beta_{ij}.$$

Estimation first requires a reduction of the parameter space. Since I do not observe miles driven, m_{is}, at the bin level, I also cannot estimate each α_{is} separately. Instead, I combine the effect of m_{is} and α_{is} into a single parameter for estimation, $\delta_{is} \equiv m_{is}\alpha_{is}$. This approach maintains flexibility across location and class in estimation, while still permitting calculation of average risks by class when applying data

TABLE 3—ESTIMATES OF $\tilde{\beta}_{ij}$ IN RESTRICTED MODEL
(*No class-level driver safety effects*)[a]

	Vehicle j:									
Vehicle i:	Compact	Midsize	Fullsize	Small luxury	Large luxury	Small SUV	Large SUV	Small pickup	Large pickup	Minivan
Compact	12.4	14.9	17.7	12.6	17.2	16.2	26.4	20.2	38.1	12.1
	(0.5)	(0.5)	(1.0)	(1.0)	(1.2)	(0.6)	(0.9)	(1.0)	(1.1)	(0.6)
Midsize	8.8	11.8	12.9	9.2	12.8	11.2	20.4	16.5	30.5	8.9
	(0.4)	(0.5)	(0.8)	(0.8)	(1.0)	(0.5)	(0.8)	(0.9)	(1.0)	(0.5)
Fullsize	8.7	11.9	16.0	8.8	14.9	11.6	19.0	17.4	30.6	9.8
	(0.7)	(0.8)	(1.5)	(1.4)	(1.9)	(0.8)	(1.3)	(1.6)	(1.6)	(1.0)
Small luxury	8.5	6.5	11.2	11.8	10.8	9.6	12.1	6.9	16.6	5.1
	(0.8)	(0.7)	(1.6)	(2.0)	(2.0)	(0.9)	(1.2)	(1.2)	(1.4)	(0.9)
Large luxury	6.6	8.7	11.6	6.1	11.2	10.3	20.4	13.3	22.9	8.2
	(0.7)	(0.8)	(1.7)	(1.5)	(2.1)	(1.0)	(1.7)	(1.7)	(1.7)	(1.1)
Small SUV	3.6	4.2	4.6	4.2	6.8	4.3	7.9	4.9	12.2	3.4
	(0.3)	(0.3)	(0.5)	(0.6)	(0.8)	(0.3)	(0.5)	(0.5)	(0.6)	(0.4)
Large SUV	4.2	4.2	3.8	3.7	5.2	3.5	7.9	5.4	11.1	3.7
	(0.3)	(0.3)	(0.6)	(0.7)	(0.8)	(0.3)	(0.6)	(0.6)	(0.7)	(0.4)
Small pickup	8.2	8.4	10.1	4.6	6.6	7.4	14.0	13.0	29.1	7.7
	(0.6)	(0.6)	(1.2)	(1.0)	(1.2)	(0.6)	(1.1)	(1.3)	(1.5)	(0.8)
Large pickup	4.8	5.2	5.9	4.5	6.3	4.4	10.1	7.4	21.5	3.6
	(0.4)	(0.4)	(0.7)	(0.7)	(0.9)	(0.4)	(0.7)	(0.7)	(1.0)	(0.4)
Minivan	3.5	3.8	6.1	3.5	3.9	5.0	8.9	7.7	14.4	4.7
	(0.3)	(0.3)	(0.8)	(0.7)	(0.8)	(0.4)	(0.7)	(0.8)	(0.9)	(0.5)

[a] Estimates are for two-car accidents, with all class-level safety effects restricted to unity. The parameters and standard errors (shown in parentheses) are computed by maximum likelihood estimation of the negative binomial version of the model. Without single-car accidents or variation over bins there are 15,600 observations and the log likelihood is $-19{,}637$. The coefficients provide a summary of fatal accident rates without controlling for driver-related risk.

on m_i ex post.[11] δ_{is} is identified up to a constant so there are $(10 \cdot 18 - 1) = 179$ of these flexible bin by class effects. The remaining parameters in the model are 100 β_{ij} terms and 18 λ_s terms. I observe the HIC score by class, h_i, and weekly counts on F_{i0s} and F_{ijs}. Pooling three years of data provides 2,808 observations on each of the 110 fatal accident types for a total of 308,880 counts.

The model for estimation is

$$F_{i0s} \sim \text{Poisson}(\omega_{is}) \tag{7}$$

$$E(F_{i0s}) = \omega_{is} = \delta_{is}\lambda_s h_i.$$

$$F_{ijs} \sim \text{Poisson}(\mu_{ijs}) \tag{8}$$

$$E(F_{ijs}) = \mu_{ijs} = \delta_{is}\delta_{js}\beta_{ij}.$$

[11] Define m_i as miles in class i summed over the set of bins S: $m_i = \sum_{s \in S} m_{is}$. Then $\left(\sum_{s \in S} \delta_{is}\right) \Big/ m_i = \left(\sum_{s \in S} m_{is}\alpha_{is}\right) \Big/ m_i \equiv \alpha_i$.

I estimate the parameters using maximum likelihood and normalize $\delta_{1,1}$ to 1. Alternative normalizations of $\delta_{1,1}$ rescale all the estimates but do not influence prediction or the ratio of estimates across classes. The Poisson dictates both the expected value and variance of the observed counts, coming from an underlying binomial.[12] A generalization allowing additional sources of error is discussed below and produces very similar estimates.

A. *Identification*

Equations (7) and (8) are estimated in combination since neither of the two is identified in isolation. λ_s and δ_{is} cannot be separated in the first equation and δ_{is} and β_{ij} cannot be separated in the second. This reflects the key identification challenge: δ_{is} contains unobserved location and driving safety behavior that we wish to separate from the risks due to vehicles themselves (assuming an average driver and location) in β_{ij}.

Algebraically, separate identification of the parameters is possible via the presence of δ_{is} in both equations and the implied cross-equation restrictions. More intuitively, the assumption I need is that factors causing δ_{is} to differ (for example a tendency to drive recklessly or in dangerous locations) simultaneously influence risk of fatal single-car accidents and fatal accidents with other cars. The λ_s parameters in (7) allow me to importantly weaken the strength of this assumption; factors contributing to single-car accidents in bin s that are common across classes are absorbed by λ_s.[13]

As an example, consider the role of dangerous rural highways; to the extent the number of single-car fatalities in the rural bins is higher than would be predicted by the HIC scores, this will be captured in a large λ_s for those bins. If after taking out λ_s there remains a particular excess of fatal accidents among pickup trucks (which is the case in the data), then the δ_{is} parameters on pickup trucks will be increased. The assumption across equations is that this part of the variation, the risk multiplier specific to pickup trucks in the rural bins, also multiplies the risks they impose in two-car accidents. Since λ_s is common to classes within a bin, my assumption is violated, for example, if the connection between single- and two-car accidents is stronger for some classes than others. I explore robustness to alternative bin structures, influencing the degree and type of flexibility allowed by the λ_s parameters, in the online Appendix.

This identification strategy is also closely related to the approach in Levitt and Porter (2001). They consider two-car accidents where neither, one, or both drivers are drunk and construct a ratio of these accident types to eliminate the latent frequency of drunk driving. In my model, a ratio of single- to two-car accidents based on (7) and (8) provides similar intuition. $F_{i0s}F_{j0s}/F_{ijs}$ eliminates unobserved driver risk in δ_{is}.

[12] If $F_{i0s} \sim \text{Poisson}(\omega_{is})$, then $\text{Var}(F_{i0s}) = E(F_{i0s}) = \omega_{is}$.

[13] Separate identification of an increase in λ_s from an increase in each of the δ_{is} terms for a bin comes from the fact the β_{ij} is by definition independent of bin; if a bin has a large number of single-car fatalities but an average number of multi-car fatalities, then a large value of λ_s and average values for the δ_{is} terms will fit the data best.

B. *Overdispersion and Error*

The Poisson specification above assumes that the only source of deviation in the count of fatal accidents across observations comes from the underlying binomial occurrence of a fatality for each vehicle mile driven. Additional sources of error will create overdispersion in the counts. The negative binomial generalization explicitly models this, adding an error component and associated variance parameter. I follow the specification of the negative binomial model given in Cameron and Trivedi (1986). The negative binomial appears in the online Appendix along with further discussion of error.

In my application, estimation of the negative binomial model produces parameter estimates that are nearly unchanged relative to the simple Poisson (the online Appendix includes the comparison). However, a likelihood ratio test does reject the Poisson and, so, I report results from the more general negative binomial throughout.

C. *Results from a Restricted Model*

For comparison I first consider a restricted model where driver-related risk and underlying engineering safety are combined into a single parameter. Dropping the terms for driver behavior reduces the model to

$$\begin{aligned} F_{ij} &\sim \text{Poisson}(\tilde{\mu}_{ij}) \\ E(F_{ij}) &= \tilde{\mu}_{ij} = m_i m_j \tilde{\beta}_{ij}, \end{aligned} \tag{9}$$

where m_i and β_{ij} are defined as before, and the ~ modifier indicates the restricted model.

Table 3 presents the estimates of $\tilde{\beta}_{ij}$ from weekly observations on F_{ij}. The restricted parameters have a simple interpretation—they are the observed fatality rates per mile in each combination of vehicle classes. The most dangerous interaction in the table occurs between compact cars and large pickup trucks, resulting in 38.1 fatalities in the compact per billion miles the two vehicles each are driven. This is about three times greater than risks from other compacts, and twice as large as risks between compacts and full-size sedans. Importantly, this table only summarizes outcomes in the data and cannot address the possibility that some classes have more fatalities due to dangerous driving behavior or locations.

Potential biases of this sort are particularly evident when examining minivans in Table 3. Minivans are much larger and heavier than the average car yet appear to impose very few fatalities on any other vehicle type, even compacts. This is noted as a puzzle in the engineering literature (Kahane 2003) since simple physics suggests minivans will cause considerable damage in collisions. I find that this is resolved by allowing flexibility in driving behavior; minivans tend to be driven much more safely, which accounts for the low rate of fatalities.

Table 4—Full Estimation Results

	Compact	Midsize	Fullsize	Small luxury	Large luxury	Small SUV	Large SUV	Small pickup	Large pickup	Minivan
α_i: Driver safety behavior[a]	1.14	0.98	1.25	1.19	1.05	0.65	1.06	1.09	1.45	0.39
	(0.06)	(0.06)	(0.08)	(0.08)	(0.07)	(0.04)	(0.06)	(0.07)	(0.08)	(0.02)
β_{ij}: Fatality rate[b] in vehicle i										
Compact	8.6	12.1	11.5	7.6	12.4	19.8	19.9	16.3	24.3	24.9
	(1.0)	(1.4)	(1.5)	(1.1)	(1.7)	(2.4)	(2.4)	(2.0)	(2.9)	(3.2)
Midsize	7.1	11.0	9.7	6.6	10.7	15.9	17.7	15.1	22.2	21.0
	(0.9)	(1.4)	(1.3)	(1.0)	(1.5)	(2.0)	(2.2)	(1.9)	(2.7)	(2.8)
Fullsize	5.6	8.9	9.5	5.2	10.1	13.0	13.0	12.5	17.5	18.2
	(0.8)	(1.2)	(1.5)	(1.0)	(1.8)	(1.8)	(1.8)	(1.8)	(2.2)	(2.8)
Small luxury	5.1	4.6	6.6	5.6	6.7	10.5	8.3	5.3	10.2	9.5
	(0.8)	(0.7)	(1.2)	(1.2)	(1.5)	(1.6)	(1.3)	(1.1)	(1.5)	(2.0)
Large luxury	4.8	7.3	7.8	3.8	8.3	13.1	15.9	11.2	15.5	17.5
	(0.8)	(1.1)	(1.5)	(1.0)	(1.9)	(2.0)	(2.3)	(2.0)	(2.2)	(3.2)
Small SUV	4.4	6.0	5.1	4.7	8.7	9.1	10.2	6.7	13.3	11.8
	(0.6)	(0.8)	(0.8)	(0.9)	(1.4)	(1.3)	(1.4)	(1.1)	(1.7)	(1.9)
Large SUV	3.1	3.7	2.6	2.5	4.0	4.6	6.2	4.5	7.3	7.9
	(0.4)	(0.5)	(0.5)	(0.6)	(0.8)	(0.7)	(0.9)	(0.8)	(1.0)	(1.3)
Small pickup	6.6	7.7	7.2	3.5	5.5	10.1	11.6	11.0	19.4	17.4
	(0.9)	(1.1)	(1.2)	(0.9)	(1.2)	(1.5)	(1.6)	(1.7)	(2.5)	(2.8)
Large pickup	3.1	3.8	3.4	2.8	4.2	4.8	6.6	4.9	11.1	6.4
	(0.4)	(0.5)	(0.5)	(0.5)	(0.8)	(0.7)	(0.9)	(0.8)	(1.4)	(1.1)
Minivan	7.3	8.9	11.3	6.5	8.3	17.7	19.0	17.4	25.9	27.1
	(1.1)	(1.3)	(2.0)	(1.6)	(1.9)	(2.6)	(2.7)	(2.8)	(3.4)	(4.7)
Negative binomial regression										
Observations	308,880									
Log likelihood	−89,321									
Wald chi2(297)	233,212									

[a] Computed using the maximum likelihood estimates of δ_{is} in equations (7) and (8), normalized such that $\sum_i \sum_s \delta_{is} = \sum_i m_i(\delta_{1,1} = 7.15)$. This makes the weighted average of α_i equal to one. Drivers of compact cars, for example, are associated with 14 percent greater risk than average.

[b] β_{ij} are rates of fatalities in car i (row) when colliding with car j (column) per billion miles traveled by average drivers. The coefficients are from estimation of equations (7) and (8), where δ_{is} is now normalized such that $\sum_i \sum_j m_i m_j \beta_{ij} = \sum_i \sum_j F_{ij}(\delta_{1,1} = 26.0)$. This makes β_{ij} comparable in magnitude to the values in Table 3. All point estimates and standard errors (shown in parentheses) are from the negative binomial version of the model.

D. *Results from the Full Model*

By combining (7) and (8) my full model is able to separate the accident rates shown in Table 3 into two pieces: the portion attributable to driver location and behavior, and the portion that comes from the physical characteristics of the vehicles themselves.

My central estimates appear in Table 4. The first row displays α_i, the average risk of drivers who select into class i taken across all bins. I choose a normalization of $\delta_{1,1}$ such that the fleet-wide average of α_i is 1 (providing easy comparison across classes). The parameters and 95 percent confidence intervals also appear graphically in Figure 1. I find that minivan drivers are the safest among all classes, with accident risks that are approximately one-third of the average. This is due both to driving behavior and the locations and times of day that minivan owners tend to be on the road. Small SUV drivers also have very low risk for fatal accidents, about half of the average. Small SUVs tend to be driven in urban areas (which are much

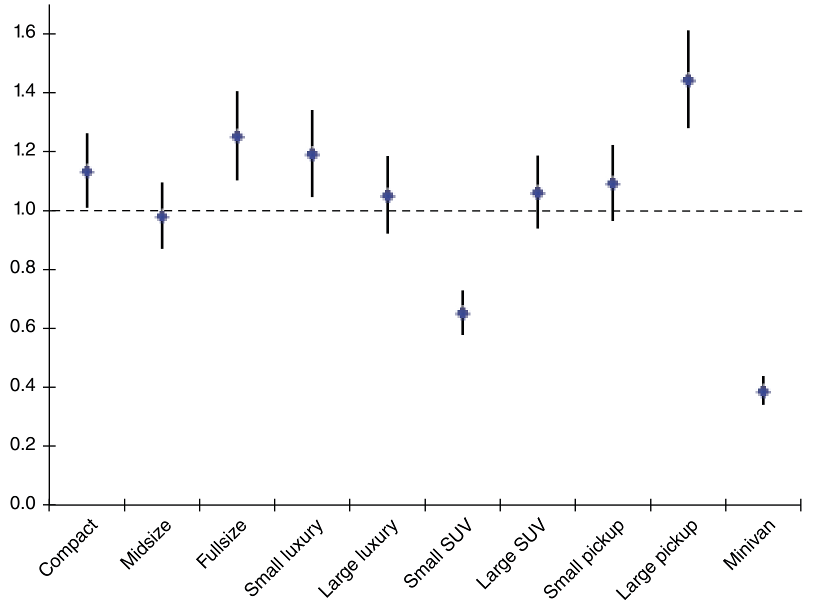

Figure 1. Estimates of α_i in Full Model[a]

[a] Values are taken from the first row of Table 4 and bars indicate 95 percent confidence intervals. The average value is normalized to one and larger values indicate more risk.

safer than rural areas in terms of fatal accidents) and are among the more expensive vehicles. I find that pickup trucks have much higher driver-related risk than SUVs of similar sizes, also intuitive given their prevalence in rural areas and younger drivers. Among passenger cars, large sedans are driven somewhat more dangerously than other car types. Again the urban rural divide may explain some of this (there are more compacts in cities) as well as the higher average age of large sedan drivers.

The next ten rows of Table 4 are my estimates of the fatality risks per mile across vehicle combinations, now assuming all vehicles have average driver-related risk. I normalize $\delta_{1,1}$ in this case such that the miles-driven weighted sum of β_{ij} predicts total fatalities (allowing comparison with $\tilde{\beta}_{ij}$ in Table 3). The change when moving from the restricted results to the full model is determined by the α terms for the two vehicles. If both classes have unusually high α parameters, for example, the β coefficient in the full model will be much smaller. I also plot the estimates of β_{ij} in Tables 3 and 4 against one other to demonstrate the overall pattern of changes. This appears in Figure 2, with the changes in pickups and minivans highlighted.

A number of key differences in β_{ij} appear between the restricted and full versions. Without accounting for driver-related risk large pickup trucks appear much more dangerous than large SUVs (compare columns 7 and 9 of Table 3). After correcting for driving safety, the two classes of vehicles now appear similar (columns 7 and 9 of Table 4). This is intuitive given their physical attributes—large SUVs and large pickups share similar weight and size, often being built on identical light truck platforms. Minivans now also look like the light trucks that they are based on (in fact

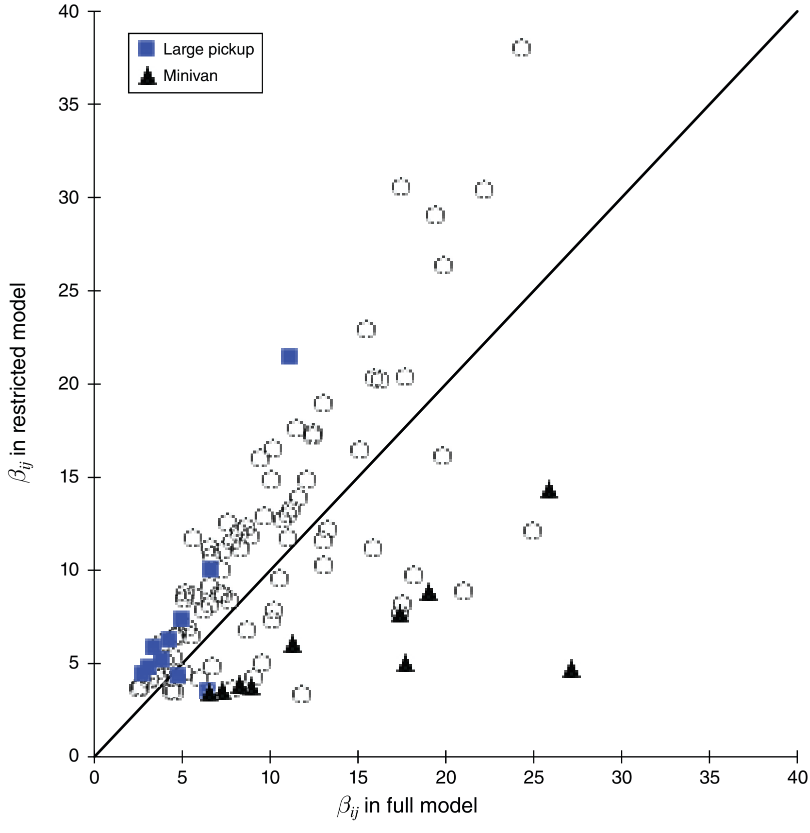

FIGURE 2. β_{ij} IN FULL MODEL[a]

[a] The 100 β_{ij} parameters from Tables 3 and 4 are plotted relative to one another. The 45-degree line represents no change across specifications and markers for large pickups and minivans (for parameters in rows i) are shown to highlight the pattern of changes. Regressing the parameters from the full model on those from the restricted model yields an R^2 of 0.47, suggesting the importance of the additional variation permitted.

becoming statistically indistinguishable from them in most accident combinations). This validates engineering predictions based on weight and size, resolving the puzzle of why they appear in so few fatal accidents.

E. β_{ij} *and the Effects of Vehicle Weight*

While this paper focuses on the policy implications of vehicle safety when combined with driver behavior, analysis of the engineering coefficients alone is also useful for context: much of the related work in engineering and economics has focused on carefully measuring the effect of vehicle weight on accident fatalities, controlling away driver behavior. In my model the effects of weight should be captured in the β_{ij} terms, though will be only a rough measure given the aggregation.

Changes in β_{ij} across the columns in Table 4 can be interpreted to reflect the external effect of a class; that is, the average number of fatalities that each class imposes on the other vehicle involved in an accident. Similarly, changes across the rows of Table 4 may be interpreted as the internal effect of that class on safety. To reduce these effects to the dimension of weight, I fit the following by least squares:

$$\ln(\beta_{ij}) = a + b \cdot weight_i + c \cdot weight_j, \tag{10}$$

where $weight_i$ is measured in thousands of pounds for the class with the fatality (making $-b$ the protective effect) and $weight_j$ is the average weight of the class without the fatality (making c the increase in risk to others). The estimate of c is 0.46 (standard error 0.065), meaning 1,000 pounds of weight increases the number of fatalities in other vehicles by about 46 percent. The average protective effect given in b suggests each 1,000 pounds of vehicle weight reduces own risk by 53 percent (standard error 6.5 percentage points). For context, the average weight in my sample is about 3,500 pounds with a standard deviation of 800. Among my 10 classes, large pickups are on average 2,000 pounds heavier than compacts.

Evans (2001) estimates both the external and internal effects of vehicle weight using differences coming only from the number of occupants in the striking and struck car. This strategy helps avoid a host of selection issues, since it exploits variation in weight holding other attributes of the vehicle fixed. He finds that 1,000 pounds increases external risk by 42 percent and decreases own risk by 40 percent. Kahane (2003) focuses on own safety risk. For passenger cars, the central estimate of the protective effect is 44 percent per 1,000 pounds of weight.[14] Kahane's estimates for light trucks, in contrast, are not robust and vary between negative 30 percent and positive 70 percent depending on accident type and vehicle size. The report speculates that the difficulty in getting consistent estimates for light trucks may be due to selection by driver type. I now have evidence to support this. The selection effects I find among different types of light trucks are much stronger than those among passenger cars.

Anderson and Auffhammer (2011) also isolate the effect of weight using a rich dataset that conditions on the occurrence of an accident (either fatal or not).[15] They find that 1,000 pounds of weight increases external risk by 47 percent. The rough estimate of the weight externality contained in my β_{ij} parameters is very similar, suggesting that, at least along the dimension of vehicle weight, the structure I impose in equations (7) and (8) has not restricted the underlying pattern in the data.

Anderson and Auffhammer use their findings to investigate the ability of gasoline taxes and weight-based mileage taxes to correct the weight externality in the fleet. In contrast, my approach allows me to consider accident risk in counterfactual fleets where the composition of vehicles and distribution of drivers across those vehicles have changed. This is ideal for analysis of the US CAFE standard and will be the focus of the policy simulations below. The two papers also take distinct

[14] The report includes a large number of estimation strategies. The central statistic I quote for cars is taken from the conclusion to chapter 3 and the results for trucks from chapter 4.

[15] Anderson and Auffhammer argue that conditioning on accident occurrence controls for most of driver selection, so remaining fatality risk can be attributed to the vehicle. This is not inconsistent with the large differences I find in α_i; since I condition on miles driven, α_i includes a tendency to get in more accidents per mile (Anderson and Auffhammer suggest this is the dominant component) while also allowing tendency toward increased severity once an accident has occurred.

approaches on empirical identification. Here it comes from the relation between single- and multi-vehicle accidents, permitting considerable flexibility in the correlation between unobserved driver characteristics and class.

IV. Policy Simulations

I now use my estimates to predict fatality rates as fleet composition changes. I will consider outcomes under three different types of fuel economy regulation, spanning current and proposed policy. The simulated changes in fleet composition will come from shadow prices implied by the different policies and a matrix of own- and cross-price elasticities taken from the literature. Changes in the fleet are largely within sample in the sense that variation is smaller than in the bins above: the fraction of large pickup trucks in the data, for example, varies from 10 percent (high income, urban, daytime) to 22 percent (low income, rural, night).

My empirical results also allow me to simulate the changing risk of individuals selecting into each vehicle type. For example, if the policy incentives cause some minivan drivers to switch to large sedans then the average risk associated with driver behavior and location should be reduced for sedans. On the other hand, if an average pickup truck driver switches to a sedan that would instead increase fatality rates in sedans all else equal. This assumes that the characteristics in α_i stay with the driver as they move across vehicles. For example geographical location (a key component of α_i), age, income, children, and alcohol use will arguably tend to stay with the driver. However, if some components of behavior interact with vehicle choice, for example along the lines of Peltzman (1975), alternative assumptions on α_i are needed. The online Appendix provides such an alternative case.

More formally, I define the driver safety multiplier in the policy cases as $\hat{\alpha}_i$ and update it with the value of α_j for all drivers switching into class i from class j.[16] Policy fleet composition is simulated by applying elasticities from Bento et al. (2009) and the shadow costs of policy. The table of elasticity estimates is available in the online Appendix where I also investigate robustness to alternative elasticities. Predicted fatalities $\hat{F}_{i0s}$ and $\hat{F}_{ijs}$ are

$$\hat{F}_{i0s} = \hat{m}_{is}\hat{\alpha}_i\lambda_s h_i \tag{11}$$

$$\hat{F}_{ijs} = \hat{m}_{is}\hat{m}_{js}\hat{\alpha}_i\hat{\alpha}_j\beta_{ij}.$$

$\hat{m}_{is}$ is the predicted fleet composition in the policy cases and will vary across the three types of fuel economy regulation I consider. Table 5 displays the shadow taxes and subsidies implicit under each of the policies I consider:

Extension of the Current CAFE Rule.—Cars and light trucks are separated into two fleets that must individually meet average fuel economy targets. The shadow

[16] Recall that α_i is an average of underlying α_{is} parameters that can vary by bin. This process assumes that vehicle demand elasticities are the same across bins so that the average switcher from each class can be accurately described by α_i.

Table 5—Average Fuel Economies and Shadow Taxes by Class

		Shadow tax of policy increment[a]		
Class	Fuel economy (MPG)	Increase current CAFE	Unified standard	Footprint CAFE
Compact	30.2	−0.28	−0.22	−0.06
Midsize	27.0	0.09	−0.12	−0.05
Fullsize	25.4	0.31	−0.06	−0.06
Small luxury	26.0	0.22	−0.08	0.02
Large luxury	23.8	0.56	0.01	0.00
Small SUV	24.1	−0.37	−0.01	0.11
Large SUV	19.0	0.44	0.28	0.14
Small pickup	22.5	−0.16	0.07	−0.02
Large pickup	19.1	0.41	0.27	−0.01
Minivan	23.4	−0.29	0.02	−0.06

[a] The implicit shadow taxes placed by fuel economy policy differ according to the type of standard. They are proportional to the distance of each vehicle (in gallons-per-mile) from the applicable fuel economy target. Units are in thousands of dollars per vehicle, though only the resulting changes in fleet composition are relevant to the safety outcomes modeled here.

taxes appear in the second column of Table 5 and are proportional to fuel economy within each fleet. Large pickups, for example, receive a shadow tax while small pickups receive a shadow subsidy. This produces a distinctive pattern of shifts to smaller vehicles within each fleet, but without substitution between cars and light trucks overall.

Single Unified Standard.—This policy places all vehicles under a single average standard. The least efficient vehicles receive the highest shadow tax and the most efficient ones receive the highest shadow subsidy. In addition to compositional shifts within cars and light trucks (as above) there is now also a broader incentive toward cars and away from light trucks in general. This type of standard was introduced in California as part of Assembly Bill 1493, and is under consideration federally.[17]

Footprint-Based CAFE Standard.—This policy assigns target fuel economies to each vehicle footprint (determined by width and wheelbase), with smaller vehicles receiving more stringent targets. The goal is to improve fuel economy without a large change in fleet composition (NHTSA 2010). The remaining effect on composition will be for classes that are either particularly efficient relative to their footprint (non-luxury cars) or particularly inefficient relative to their footprint (SUVs). This creates the relatively small incentives appearing in the final column of Table 5. The aggregation up to class level in my model presents a caveat that is important here. If the correlation between weight and fuel economy is low for vehicles within the same class, then the footprint standard may also cause more finely detailed compositional changes that are not captured.

[17] Strictly speaking the California bill preserves the fleet definition, but allows manufacturers to trade compliance obligations between fleets in order to achieve a single average target. The trading between fleets aligns incentives for all vehicles, making the rule act like a single standard.

I model an increment to fuel economy of one MPG for each policy and consider long-run changes throughout the fleet. Since these policies also create incentives for engine efficiency improvements (which presumably do not influence safety directly), I will assign only a portion of the overall fuel savings to composition. In particular, the tables below provide the safety impacts of a 0.1 MPG change achieved through composition with the remaining 0.9 allowed to come via changes that do not affect safety. Alternative assumptions on this division can be easily accommodated by scaling the results by the fraction of savings assumed to come via composition.

My simulation also abstracts from possible changes in total travel demand, holding miles driven fixed at 2009 levels. In practice, two countervailing effects may be present: fuel economy rules likely increase travel in any one car (the "rebound" effect when fuel cost declines) and decrease the number of cars sold (since average vehicle price rises). My results could again be scaled up or down according to any projected changes in aggregate miles driven.

Finally, I make two simplifying assumptions to account for commercial vehicles and pedestrians. I assume that the number of commercial vehicles remains fixed since they are not covered by CAFE regulation. Fatalities due to collisions with commercial vehicles make up about 8.4 percent of fatalities (NHTSA 2009) and I model changes using the same risk factors I estimate for single-car accidents.[18] Second, I assume a constant fatality rate for pedestrians based on the observation that current rates are nearly identical among cars and light trucks.[19] To the extent that smaller vehicles reduce pedestrian fatalities, for example because of better visibility when reversing, it will accentuate the benefits of the uniform policy that I identify below.

A. *Results*

Tables 6–8 correspond to each of the three policy types and estimate the change in fatalities per year for a 1 MPG improvement in fuel economy. Standard errors reflect the estimates of the safety parameters made in this paper; the hypothetical changes in policy and fleet composition are treated as deterministic. The online Appendix includes an extension incorporating uncertainty in the pattern of composition changes.

Increment to Current CAFE Rules.—The left panel of Table 6 displays the change in total traffic deaths predicted using the restricted model (not accounting for driver behavior or selection). The restricted model suggests that CAFE offers a safety improvement of 135 fewer fatalities per year.

A very different picture emerges from the full model, where the increment to CAFE is instead estimated to result in 149 additional fatalities per year. The final

[18] The much larger mass of commercial trucks means collisions with them resemble single-car accidents with fixed objects. Making the alternative assumption, that risk in accidents with commercial vehicles is unchanged, has very little effect on the overall results.

[19] Pedestrian fatalities in my data are 2.82 per billion miles for cars and 2.81 per billion miles for light trucks. Within trucks, fatality rates are somewhat higher for larger vehicles. Perhaps surprisingly, the opposite is true for cars.

Table 6—Effect of an Increase in Current CAFE Rules on Total Traffic Deaths

	No driver effects[a]			Full model[b]		
	One car	Two car	Total	One car	Two car	Total
Compact	226.3	142.4	368.6	236.1	177.6	413.6
Midsize	−60.1	−75.4	−135.5	−51.3	−50.6	−101.9
Fullsize	−55.0	−57.0	−112.0	−55.1	−51.0	−106.1
Small luxury	−30.8	−16.1	−46.8	−30.9	−13.4	−44.2
Large luxury	−34.6	−25.6	−60.2	−34.6	−22.3	−57.0
Small SUV	78.4	16.4	94.8	142.4	45.3	187.7
Large SUV	−85.9	−27.1	−113.0	−85.8	−23.2	−109.0
Small pickup	47.8	11.9	59.7	50.9	18.4	69.3
Large pickup	−168.7	−54.6	−223.2	−171.4	−50.8	−222.3
Minivan	22.4	10.2	32.6	69.1	50.2	119.3
Total	−60.0	−75.0	**−135.0**	69.3	80.2	**149.5**
Standard error[c]			(6.1)			(9.4)
Cost of risk change (millions)[d]		−932		1,031		

[a] This case reflects the restricted model. Driving safety behavior is assumed constant across all classes and only the quantity of cars in each class changes. The change in fatalities is expressed per year for a one-MPG increment to fuel economy rules.

[b] Here the full model is used to predict changes in safety, now accounting for differences in driving safety behavior across classes.

[c] The variance of simulation results G is approximated by $(\partial G(\hat{\gamma})/\partial \hat{\gamma})' \,\mathrm{Var}(\hat{\gamma})(\partial G(\hat{\gamma})/\partial \hat{\gamma})$ where $\mathrm{Var}(\hat{\gamma})$ is the variance-covariance matrix from estimation of the negative binomial model and the vector $\hat{\gamma}$ includes the estimated λ_i, β_{ij}, and δ_{is} parameters.

[d] Annual costs in millions of dollars calculated as the change in total fatality risk multiplied by a value of statistical life of \$6.9 million.

row applies the value of statistical life figure used in EPA benefit-cost analyses to convert this change in risk to dollar cost, exceeding \$1 billion annually. Assuming 2 trillion miles driven and an average fuel economy of 25 MPG, the policy will save roughly 3.2 billion gallons of gasoline annually. This amounts to 33 cents per gallon saved.

The reversal in sign when applying the full model follows directly from the estimates of α_i: large SUVs and pickups (and large sedans) cause and experience a lot of fatal accidents in the data. The naïve restricted model assumes that when you take away these large (and seemingly dangerous) vehicles an improvement in safety results. Unfortunately I must argue that the picture is not so favorable. Much of the danger in the larger vehicle classes appears to be due to their drivers, not the cars themselves.

It is important to reiterate that the driver effects here are not all (or even predominantly) things we would fault drivers for. Data in the online Appendix on fault suggests a significant portion is likely to come instead through geography and the urban rural split: drivers who currently choose large vehicles tend to live in rural areas where accident fatality rates are already very high. As these drivers change to smaller vehicles the dangers of rural highways remain. This effect appears in $\hat{\alpha}_i$.

One key caveat in the simulation results comes in aggregation. I implicitly assume that substitution within classes has a similar effect to substitution between classes. Detail on the aggregation and class definitions also appears in the online Appendix.

Table 7—Effect of a Unified Fuel Economy Standard on Total Traffic Deaths[a]

	No driver effects			Full model		
	One car	Two car	Total	One car	Two car	Total
Compact	167.8	105.7	273.5	153.3	97.7	251.0
Midsize	39.4	7.5	47.0	44.7	13.9	58.6
Fullsize	6.7	−1.5	5.2	5.6	−1.6	4.0
Small luxury	5.7	0.8	6.5	4.9	0.7	5.6
Large luxury	−2.6	−5.6	−8.1	−2.1	−4.8	−6.9
Small SUV	−12.5	−11.8	−24.3	−0.3	-6.7	−7.0
Large SUV	−62.1	−19.6	−81.7	−62.1	−19.1	−81.2
Small pickup	−32.6	−20.4	−53.0	−32.3	−19.7	−52.0
Large pickup	−122.4	−39.2	−161.6	−122.9	−38.9	−161.8
Minivan	−5.6	−10.0	−15.6	2.0	−3.8	−1.8
Total	−18.0	5.9	**−12.1**	−9.3	17.8	**8.5**
Standard error[c]			(3.8)			(4.3)
Cost of risk change (millions)[d]			−84			59

[a] The unified standard induces two kinds of changes in the fleet: (i) Small vehicles replace large ones within the car and light truck divisions. (ii) Light trucks overall (the second set of five classes) replace cars overall (the first group). The change is expressed in fatalities per year for a one-MPG increment to fuel economy rules and standard errors are calculated as in Table 6.
[b] In millions of dollars annually.

Unified Standard.—Table 7 presents the strikingly different outcome from a unified standard. My full model shows an increase of only eight fatalities per year, and a zero change lies within the confidence bounds. This represents a highly statistically significant improvement over current CAFE rules and comes as the result of two effects canceling each other out in the fleet. The first is the deterioration in safety due to changes within the car and light truck fleets, as above. The second, countervailing effect comes from the switch away from light trucks and into cars, also incentivized by a uniform CAFE rule. My empirical estimates contain information on the relative importance of these two effects and under a unified CAFE standard I find that they offset almost exactly.

Footprint-Based Standard.—Table 8 presents results for the footprint-based standard. The small changes in fleet composition under this policy correspond to only a small deterioration in safety. However, the limited safety effects come paired with large efficiency costs. In this case, fuel savings under the footprint standard must be accomplished almost exclusively through engine technology. Movement to a smaller and lighter fleet is likely to be a much cheaper way to save gasoline, and that channel is shut down by the new rules.[20]

My results on the unified standard above are encouraging in this regard. I show that savings in gasoline from movement to a smaller fleet can come with the same minimal effect on safety that appears under the footprint standard.

[20] Depending on the slope of the relation between footprint and the fuel economy requirement (and differences between cars and light trucks), this policy could still create some compositional changes. The net effect would then become intermediate to the other policies I examine.

Table 8—Effect of a Footprint Fuel Economy Standard on Total Traffic Deaths[a]

	No driver effects			Full model		
	One car	Two car	Total	One car	Two car	Total
Compact	45.6	31.4	77.0	38.0	24.4	62.4
Midsize	15.9	8.5	24.4	15.0	6.9	21.9
Fullsize	8.9	6.7	15.6	7.3	5.0	12.3
Small luxury	−3.4	−1.9	−5.3	−3.9	−2.3	−6.2
Large luxury	−0.5	−1.2	−1.7	−0.8	−1.5	−2.2
Small SUV	−31.6	−12.5	−44.1	−31.3	−12.7	−44.0
Large SUV	−32.6	−8.7	−41.3	−32.6	−8.9	−41.5
Small pickup	1.8	0.3	2.1	0.9	−0.4	0.5
Large pickup	−4.1	−2.0	−-6.2	−10.0	−4.0	−14.0
Minivan	4.1	2.2	6.4	10.3	6.8	17.1
Total	4.2	22.7	**26.9**	−7.1	13.4	**6.3**
Standard error[c]			(1.3)			(1.5)
Cost of risk change (millions)[d]			185			43

[a] A footprint standard (by design) involves much smaller changes in the composition of the fleet than either of the first two policies. The changes in accident fatalities are similarly small. The change is again expressed in fatalities per year for a one-MPG improvement and standard errors are as above.
[b] In millions of dollars annually.

V. Alternative Models

The first two columns of Table 9 provide a summary of the results above, with the remaining columns investigating robustness to a group of alternative models.

Column 3 presents results using an alternative source for vehicle demand elasticities. In contrast to the cross-sectional demand variation used above, Kleit (2004) derives elasticities from survey data on second choices of new car owners. My simulation results are robust. Both elasticity matrices are included in the online Appendix.

Next, I consider a variation of my main parameter estimates, where α_i and β_{ij} are identified without the use of crash test data. I instead rely on the physical property that accidents between two vehicles of similar mass and speed closely resemble accidents with fixed objects, since both result in rapid deceleration to a stationary position.[21] In this setting, single car fatalities will be proportional to those in accidents between cars of the same class, β_{ii}. The model in Section I becomes

$$E(F_{i0s}) = m_{is}\alpha_{is}\lambda_s\beta_{ii} \tag{12}$$

$$E(F_{ijs}) = m_{is}m_{js}\alpha_{is}\alpha_{js}\beta_{ij}.$$

Column 4 of Table 9 shows the results from estimating (12). The results on existing CAFE and the unified standard confirm those in the main specification, though standard errors are much larger, reflecting the reduction in data available to the model. In contrast to the main model, the footprint standard now suggests

[21] See Greene (2009). Each vehicle's change in velocity raised to the fourth power closely predicts injury severity.

Table 9—Alternative Models and Subsamples of the Data

	No driver effects	Full model (central)	Alternative elasticities[a]	Alternative identification[b]	1998 and newer[c]	Drivers 55 and under[c]	Clear weather[c]
Current CAFE within fleet	−135.02	149.47	156.15	222.00	142.15	137.14	148.52
	(6.15)	(9.36)	(10.38)	(53.97)	(10.83)	(9.41)	(10.00)
Unified standard	−12.14	8.50	32.97	7.31	6.27	−1.15	8.26
	(3.81)	(4.35)	(2.85)	(21.11)	(5.21)	(4.33)	(4.62)
Footprint-based standard	26.88	6.27	8.18	−47.55	0.56	3.97	6.99
	(1.28)	(1.52)	(1.27)	(5.72)	(1.85)	(1.58)	(1.62)

[a] The alternative substitution elasticities are taken from Kleit (2004).
[b] The alternative identification strategy removes the need for crash test data. The standard errors are much larger given the additional cross-equation restrictions.
[c] Changes in overall safety through time (perhaps most importantly the airbag requirement in 1998) do not affect the relative safety performance of classes enough to alter my conclusions on fuel economy rules. The potential frailty of older drivers and selection of vehicle type by weather conditions have similarly small impacts on the results.

an improvement in safety that can be traced back to relatively high fatality rates in SUV-SUV collisions.[22]

I also consider robustness of my results in three subsamples of the data suggested by prior work on safety. Total fatalities are divided by the fraction of observations included to make magnitudes comparable across columns. Column 5 of the table restricts the sample to 1998 and newer models, ensuring that all vehicles have airbags. Airbags dramatically reduce fatality risks, and if their presence also influences driving behavior or changes relative risk across classes, we might expect a different set of results to emerge. My estimates, however, appear robust in this dimension.

Column 6 examines the subsample of drivers aged 55 and under. Loughran and Seabury (2007) show that elderly drivers may more often be the subjects of fatal traffic accidents due to their relative frailty, potentially introducing an asymmetry in my model if they do not also impose greater risk on those around them. The result, however, suggests these effects offset or are relatively small in the context of fleet changes from CAFE.

I limit the sample in the final column of Table 9 to remove accidents where any adverse weather condition is recorded. If the fatality pattern across classes is importantly different for bad-weather accidents this could confound estimates after vehicle choice changes with CAFE. My results are again unchanged, reflecting in part the fact that most fatal accidents (about 90 percent) occur in clear weather.

Finally, I consider the possibility of interactions between driving behavior and the vehicle's own safety. Peltzman (1975) argues that safer vehicles will be driven more aggressively as a result of the driver's tradeoff in utility. Cohen and Einav (2003) subsequently show the effect is empirically quite small, though I investigate it here in the event it could remain important for CAFE. When including an upper bound on the size of the Peltzman effect (computed in the Appendix), the policy results become more optimistic across cases. A Peltzman effect implies that average driving

[22] The fatality rate in matched SUV collisions is large relative to that expected from crash tests, perhaps due to increased rollover risk. The resulting beta coefficients on SUVs are 13 percent larger, which translates to the gain when SUVs are discouraged by the footprint rule.

behavior in the fleet is improved when people are moved to smaller vehicles. I predict 102 additional fatalities under existing standards (as opposed to 149 in the main model) and a reduction of 64 fatalities under the unified standard. The safety gain from moving to a unified standard remains robust, in fact growing somewhat larger.

VI. Conclusions

I employ data on fatal traffic accidents to estimate driver-related risks and the underlying physical risk associated with different vehicle classes. I capture unobserved driver location and behavior alongside a flexible specification of fatality risk for all combinations of classes. The estimates have application to fuel economy policy, studied here, and also to a much broader set of policy initiatives. I show that correctly accounting for driver behavior significantly alters conclusions about fleet composition and safety.

Two key patterns appear in the empirical estimates. First, there is considerable diversity in driving behavior across vehicle classes. The most dangerous drivers (pickup truck owners) are nearly four times as likely to be involved in fatal accidents as the safest drivers (minivan owners) after controlling for the physical safety attributes of their vehicles. Second, controlling for driver safety produces estimates of the physical safety of vehicles that closely mirrors theoretical engineering results. Larger and heavier vehicle classes are the safest to be inside during an accident but also impose much greater risk on others in the fleet.

The specific estimates I recover for each class address the motivating question relating safety and fuel economy regulation. I find that the separation of light trucks and SUVs from passenger cars in existing CAFE regulation is harmful to safety. Incrementing the standards by one MPG causes an additional 149 fatalities per year in expectation. The increase in statistical risk would be valued at 33 cents per gallon of gasoline saved, with injuries and property damage (assuming they are correlated with fatalities) further increasing the cost of this type of fuel economy rule. Intuitively, my estimates measure the degree to which greater diversity in the vehicle fleet leads to more fatal accidents. Current CAFE standards, by encouraging light trucks while at the same time making passenger cars smaller and lighter, increase the diversity of the fleet.

In contrast, I find that a unified fuel economy standard has almost no harmful effect on safety. Two effects operate in opposing directions: weight reductions increase risk while substitution away from light trucks makes the fleet more homogeneous reducing the number of dangerous interactions. I find that these effects offset almost exactly under a uniform fuel economy standard.

While my simulations focus on different types of fuel economy regulation (the primary tool in US gasoline policy), a key concern of the prior literature has been comparison with gasoline taxes. Because the compositional effect of a gasoline tax is similar to my unified standard, I can offer an approximate calculation of the safety impacts. The details appear in the online Appendix, with the key finding that there is almost no safety cost from compositional change under a gasoline tax. Further, the reduction in driving under a tax offers the potential for significant reductions in safety cost.

Additional extension of the simulations could allow analysis of a variety of other current and proposed policies influencing the car market. For example the US "cash-for-clunkers" program as described in Knittel (2009) or incentives to switch among new and used vehicles in Busse, Knittel, and Zettelmeyer (2009) produce changes in the fleet that may also have large safety effects.

Several important limitations in my estimates remain: a disaggregation of car classes, for example, by manufacturer, fuel economy, or footprint, could identify more finely grained changes within the current class definitions. Incorporating forecasts for the evolution of the fleet over time could reveal short run impacts on safety, and a longer series of data on miles driven might allow improved precision and estimates of the change in relative safety of different classes through time.

REFERENCES

Ahmad, Sanjana, and David L. Greene. 2005. "Effect of Fuel Economy on Automobile Safety: A Reexamination." *Transportation Research Record: Journal of the Transportation Research Board* 1941: 1–7.

Anderson, Michael. 2008. "Safety for whom? The effects of light trucks on traffic fatalities." *Journal of Health Economics* 27 (4): 973–89.

Anderson, Michael, and Maximilian Auffhammer. 2011. "Pounds That Kill: The External Costs of Vehicle Weight." National Bureau of Economic Research (NBER) Working Paper 17170.

Anderson, Soren T., and James M. Sallee. 2011. "Using Loopholes to Reveal the Marginal Cost of Regulation: The Case of Fuel-Economy Standards." *American Economic Review* 101 (4): 1375–1409.

Austin, David, and Terry Dinan. 2005. "Clearing the Air: The Costs and Consequences of Higher CAFE Standards and Increased Gasoline Taxes." *Journal of Environmental Economics and Management* 50 (3): 562–82.

Bento, Antonio M., Lawrence H. Goulder, Mark R. Jacobsen, and Roger H. von Haefen. 2009. "Distributional and Efficiency Impacts of Increased US Gasoline Taxes." *American Economic Review* 99 (3): 667–99.

Busse, Meghan R., Christopher R. Knittel, and Florian Zettelmeyer. 2013. "Are Consumers Myopic? Evidence from New and Used Car Purchases." *American Economic Review* 103 (1): 220–56.

Cohen, Alma, and Liran Einav. 2003. "The Effects of Mandatory Seat Belt Laws on Driving Behavior and Traffic Fatalities." *Review of Economics and Statistics* 85 (4): 828–43.

Cameron, A. Colin, and Pravin K. Trivedi. 1986. "Econometric Models Based on Count Data. Comparisons and Applications of Some Estimators and Tests." *Journal of Applied Econometrics* 1 (1): 29–53.

Crandall, Robert W., and John D. Graham. 1989. "The Effect of Fuel Economy Standards on Automobile Safety." *Journal of Law and Economics* 32 (1): 97–118.

Evans, Leonard. 2001. "Causal Influence of Car Mass and Size on Driver Fatality Risk." *American Journal of Public Health* 91 (7): 1076–81.

Federal Highway Administration. 2009. "2009 National Household Travel Survey: vehmiles." U.S. Department of Transportation. http://nhts.ornl.gov/2009/download/Dbf.zip (accessed September 1, 2012).

Gayer, Ted. 2004. "The Fatality Risks of Sport-Utility Vehicles, Vans, and Pickups Relative to Cars." *Journal of Risk and Uncertainty* 28 (2): 103–33.

Goldberg, Pinelopi Koujianou. 1998. "The Effects of the Corporate Average Fuel Efficiency Standards in the US." *Journal of Industrial Economics* 46 (1): 1–33.

Greene, David L. 2009. "Feebates, Footprints and Highway Safety." *Transportation Research Part D: Transport and Environment* 14 (6): 375–84.

Herman, Irving P. 2007. *Physics of the Human Body*. New York: Springer.

Jacobsen, Mark R. Forthcoming. "Evaluating U.S. Fuel Economy Standards in a Model with Producer and Household Heterogeneity." *American Economic Journal: Economic Policy*.

Jacobsen, Mark R. 2013 "Fuel Economy and Safety: The Influences of Vehicle Class and Driver Behavior: Dataset." *American Economic Journal: Applied Economics*. http://dx.doi.org/10.12357/app.5.3.1.

Kahane, Charles J. 2003. *Vehicle Weight, Fatality Risk and Crash Compatibility of Model Year 1991–99 Passenger Cars and Light Trucks*. Department of Transportation, National Highway Traffic Safety Administration Technical Report 809 662. Washington, DC, October.

Khazzoom, J. Daniel. 1994. "Fuel Efficiency and Automobile Safety: Single-Vehicle Highway Fatalities for Passenger Cars." *Energy Journal* 15 (4): 49–101.

Kleit, Andrew N. 2004. "Impacts of Long-Range Increases in the Corporate Average Fuel Economy (CAFE) Standard." *Economic Inquiry* 42 (2): 279–94.

Klier, Thomas, and Joshua Linn. Forthcoming. "New Vehicle Characteristics and the Cost of the Corporate Average Fuel Economy Standard." *RAND Journal of Economics*.

Knittel, Christopher R. 2009. "The Implied Cost of Carbon Dioxide under the Cash for Clunkers Program." Center for the Study of Energy Markets Working Paper 189.

Levitt, Steven D., and Jack Porter. 2001. "How Dangerous Are Drinking Drivers?" *Journal of Political Economy* 109 (6): 1198–1237.

Li, Shanjun. 2012. "Traffic Safety and Vehicle Choice: Quantifying the Effects of the 'Arms Race' on American Roads." *Journal of Applied Econometrics* 27 (1): 34–62.

Loughran, David S., and Seth A. Seabury. 2007. *Estimating the Accident Risk of Older Drivers.* Santa Monica: RAND Institute for Civil Justice.

National Highway Traffic Safety Administration. 1992–2008. "Vehicle Crash Test Database: HIC score." U.S. Department of Transportation. http://www-nrd.nhtsa.dot.gov/database/reh.reh.htm (accessed September 1, 2012).

National Highway Traffic Safety Administration. 2006–2008. "Fatality Analysis Reporting System: Accident, Vehicle and Person tables." US Department of Transportation. http://www-fars.nhtsa.dot.gov/Main/index.aspx (accessed September 1, 2012).

National Highway Traffic Safety Administration. 2008. *National Motor Vehicle Crash Causation Survey: Report to Congress*. U.S. Department of Transportation HS 811 059. Washington, DC, July.

National Highway Traffic Safety Administration. 2009. *Traffic Safety Facts: A Brief Statistical Summary*. U.S. Department of Transportation HS 811 172. Washington, DC, June.

National Highway Traffic Safety Administration, and Environmental Protection Agency. 2010. "Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards; Final Rule." *Federal Register* 75 (88): 25324–728.

National Research Council. 2002. *Effectiveness and Impact of Corporate Average Fuel Economy* (*CAFE*) *Standards*. Washington, DC: National Academy Press.

Noland, Robert B. 2004. "Motor Vehicle Fuel Efficiency and Traffic Fatalities." *Energy Journal* 25 (4): 1–22.

Parry, Ian W. H., and Kenneth A. Small. 2005. "Does Britain or the United States Have the Right Gasoline Tax?" *American Economic Review* 95 (4): 1276–89.

Peltzman, Sam. 1975. "The Effects of Automobile Safety Regulation." *Journal of Political Economy* 83 (4): 677–726.

Portney, Paul R., Ian W. H. Parry, Howard K. Gruenspecht, and Winston Harrington. 2003. "Policy Watch: The Economics of Fuel Economy Standards." *Journal of Economic Perspectives* 17 (4): 203–17.

Wenzel, Thomas P., and Marc Ross. 2005. "The effects of vehicle model and driver behavior on risk." *Accident Analysis and Prevention* 37 (3): 479–94.

White House Office of the Press Secretary. 2011. *President Obama Announces Historic 54.5 mpg Fuel Efficiency Standard*. Media release, Washington, DC, July 29, 2011. http://www.whitehouse.gov/the-press-office/2011/07/29/president-obama-announces-historic-545-mpg-fuel-efficiency-standard.

White, Michelle J. 2004. "The 'Arms Race' on American Roads: The Effect of Sport Utility Vehicles and Pickup Trucks on Traffic Safety." *Journal of Law and Economics* 47 (2): 333–55.