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FUEL ECONOMY AND SAFETY: THE INFLUENCES OF VEHICLE CLASS AND DRIVER BEHAVIOR

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Abstract

Fuel economy standards change the composition of the vehicle fleet – typically increasing the number of small vehicles – potentially influencing the number of fatalities in car accidents. I introduce a novel way to estimate the safety impacts of changes in vehicle class composition, simultaneously recovering estimates of driving safety behavior and the influence of vehicle characteristics on accident outcomes. I find that modeling driver behavior is critical to understanding the impacts of policy, and demonstrate that the inclusion of driver effects can reverse the sign of fuel economy standards' effect on safety. I show that driver risks vary by a factor of three across ten classes spanning all U.S. passenger vehicles. Incorporating these new estimates in a model of fuel economy rules, I find that the present distinction between light trucks and cars has negative consequences for overall safety: Each MPG increment to the standard results in an additional 149 fatalities per year in expectation. I then show how two alternative regulatory provisions can produce near-zero changes in accident fatalities, intuitively balancing reduction of an "arms race" effect against the risks in single-vehicle accidents.

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1. Introduction

Fuel economy standards create an incentive for manufacturers to alter the composition of the vehicle fleet toward smaller and lighter vehicles, potentially changing vehicle safety. This issue has been the source of strident political debate and has been made increasingly salient by a dramatic 35 percent increment to the standards set for 2020.[1]

Estimating the costs of fuel economy policy in terms of safety requires two sets of parameters: i) The influence of engineering characteristics (e.g. height, weight and wheelbase) on degree of injury in accidents, and ii) a measure of the riskiness of the drivers who select different types of vehicles.[2] Fuel economy standards change not only the composition of vehicles in the fleet but also the average riskiness of the drivers in each type of vehicle. To see this, consider a very safe minivan driver who switches to a large sedan as the result of fuel economy incentives. The switch will act to improve the average safety of sedan drivers, reducing the expected number of fatalities in sedans all else equal.

I introduce a technique to estimate both sets of parameters simultaneously using data on accident fatalities. I capture driver safety as a residual term, allowing both observable and unobservable factors to enter my estimates of driving behavior. My estimates of the physical safety of vehicles – with driver behavior held constant – are semi-parametric and include the influence of vehicle type on both the safety of the occupant as well as the safety of those in other vehicles struck in the accident. To my knowledge mine is the first study to explicitly estimate driving behavior along with the own and external safety impacts of physical vehicle characteristics in a single step. Doing so allows me to reconcile conflicting evidence from the prior research and conduct new policy simulations that explicitly include the effects of driver behavior.

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[1] The Energy Independence and Security Act of 2007 and Environmental Protection Agency (2009).

[2] Some of driving safety is well-known to be correlated with observables like age, gender, and income. Important factors that are generally not observed include the tendency to drive drunk, the time of day driving occurs, types of roads used, disregard for traffic signals, or simply taste for safety. Levitt and Porter (2001) estimate drunk driving rates using innocent vehicles in accidents as control, but in most cases the personal characteristics that go into driving safety are quite difficult to measure.

The literature in this area has often focused on a particular physical characteristic of vehicles, typically weight, controlling away the effects of driver behavior. Kahane (2003) and the National Research Council (2002) provide summaries. Evans (2001) and Anderson and Auffhammer (2011) go to particular lengths to control for driver behavior in their data, estimating the own and external effects of weight in isolation. They show that heavier vehicles offer additional protection for their occupants at the cost of increasing the risk to other vehicles in an accident. White (2004) and Gayer (2004) reach a similar conclusion when considering the increasing popularity of ever-heavier SUV's, calling the effect an "arms race." These studies suggest that fuel economy standards could reduce the weight externality, potentially improving overall safety.

In contrast, The National Research Council (2002) summarizes a second set of studies on weight and estimates that 2,000 additional deaths annually are associated with reductions in vehicle weight to meet existing fuel economy standards.[3] The fact that lighter vehicles tend to perform more poorly in single-car accidents and crash tests lends support to this finding, and it is cited as evidence of the high cost of fuel economy rules.

In this paper I instead choose to abstract from any single attribute and consider ten classes of vehicle that span the fleet. Among other dimensions, they differ in weight, height, wheelbase, fuel economy, and passenger capacity. I measure the safety impact that each of the ten classes has on every other – finding a large arms race component – as well as the risks of each class in single-car accidents. I combine these results with my estimates of driver behavior, and measure the effect of the fleet composition changes associated with fuel economy standards on overall safety outcomes across driver types and vehicle classes.

The simulations yield intuitive and robust results: heterogeneity of vehicle types is associated with larger fatality risk, and current fuel economy standards increase heterogeneity by incentivizing pickup trucks and SUV's while simultaneously causing a switch toward smaller and lighter classes of passenger car. I therefore find that the current standards increase overall accident risks. I next examine a unified standard and find reason for optimism: a unified fuel economy rule encourages switching out of all larger and heavier

[3] See Portney et al (2003) and Crandall and Graham (1989) for further discussion.

classes, including pickups and SUV's, and is able to achieve a neutral safety outcome. I find that the gains a unified standard achieves by reducing the arms race effect are just offset by the somewhat worse outcomes in single and same-car accidents.

I make two main contributions in this paper: The first is in estimation of driver behavior by vehicle type, which I separate from the effects of physical characteristics by incorporating single-vehicle accidents and crash test results. I find that Minivans and SUV's are associated with safer-than-average driving, corresponding to the concentration of families, highly educated households, and urban drivers in these vehicle types. Pickup trucks and large sedans are associated with higher risk driving, corresponding to the extremes in age distribution of their drivers. The second contribution is in the underlying safety estimates and policy simulations: I identify the source of increased fatality risk under current fuel economy rules and demonstrate that a simple change can neutralize the adverse safety outcomes while still meeting the goal of reduced gasoline consumption.

The rest of the paper is organized as follows: Section 2 describes U.S. fuel economy policy and the role of safety. Section 3 presents my empirical strategy. Sections 4 and 5 respectively describe the data and empirical results. Section 6 presents the policy experiments, combining my empirical results with a model of fuel economy regulation. The final sections introduce two alternative models, address robustness, and conclude.

2. Safety and Fuel Economy Regulation

The importance of small changes to fleet safety

The importance of automobile safety is evident simply from the scale of injuries and fatalities each year. In 2008 there were 37,261 fatalities in car accidents on U.S. roads and more than 2.3 million people injured.[4] The National Highway Traffic Safety Administration (NHTSA) is tasked with monitoring and mitigating these risks and oversees numerous federal regulations that include both automobiles and the design of roads and signals.

[4] NHTSA (2009).

To further motivate the concern about fuel economy standards with respect to safety consider the very rough estimate provided in NRC (2002): Approximately 2,000 of the traffic fatalities each year can be attributed to changes in the composition of the vehicle fleet due to the Corporate Average Fuel Economy (CAFE) standards. If we further assume that the standards are binding by about 2 miles per gallon, this translates to a savings of 7.5 billion gallons of gasoline per year. Valuing the accident risks according to the Department of Transportation's methodology this implies a cost of $1.55 per gallon saved through increased fatalities alone.[5] This does not consider injuries, or any of the other distortions associated with fuel economy rules, yet by itself exceeds many estimates of the externalities arising from the consumption of gasoline.

Conversely, a finding that accident risks improve with stricter fuel economy regulation (along the lines of the work mentioned above that stresses the dangers of large vehicles) would present an equally strong argument in favor of stringent fuel economy rules. The magnitude of the implicit costs involved in vehicle safety motivate the importance of a careful economic analysis, and mean that even small changes in the anticipated number of fatalities will carry great weight in determining the optimal level of fuel economy policy.

Current regulation

U.S. fuel economy regulation is in transition and the form of the rule beyond 2016 has not been determined. I consider three possible regulatory regimes, each of which produces a unique effect on the composition of the fleet. The resulting impacts on the frequency of fatal accidents are similarly diverse:

1) The current Corporate Average Fuel Economy (CAFE) rules: Light trucks and cars are separated into two fleets, which must individually meet average fuel economy targets. No direct incentive exists for manufacturers to produce more vehicles in one fleet than the other. Rather, the incentives to change composition occur inside each fleet: selling more small

[5] The Department of Transportation currently incorporates a value of statistical life of $5.8 million in their estimates. This is conservative relative to the $6.9 million used by EPA.

trucks and fewer large trucks improves the fuel economy and compliance of the truck fleet. The same is true inside the car fleet. This produces a distinctive pattern of shifts to smaller vehicles within each fleet, but without substitution between cars and trucks overall.

2) A unified standard: This type of standard has been introduced in California as Assembly Bill 1493, and is under consideration federally.[6] It regulates all vehicles together based only on fuel economy. This has the effect of encouraging more small vehicles, broadly shifting the fleet away from trucks and SUV's and into cars.

3) A "footprint" standard: This type of rule is in place federally for the years 2012 - 2016 and is presently being debated for the years 2017 through 2020. It assigns target fuel economies to each size of vehicle (as determined by width and wheelbase), severely limiting the incentives for any change in fleet composition. As such it increases the technology costs of meeting a given target, but was required in the hopes of mitigating the costly safety consequences discussed above.[7]

3. A Model of Accident Counts

I model the count of fatal accidents between each combination of vehicle classes as a Poisson random variable. Vehicle classes in the data represent various sizes and types of cars, trucks, SUV's and minivans; covering all passenger vehicles in the U.S.

Define Z_{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 data will be asymmetric, that is $Z_{ij} \neq Z_{ji}$, to the degree that some vehicle classes impose a greater external risk on others. In the relatively unusual cases where a fatality occurs in both vehicles in an accident then both Z_{ij} and Z_{ji} are incremented.

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[6] 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.
[7] NHTSA (2008b) discusses the rationale for the footprint rule. Technology costs are higher because all improvement must be achieved through technology; the other rules allow some of the improvement to come from technology and some to come via fleet composition.

We can write the total count of fatalities in vehicles of class i as:

$$\text{(fatalities in class i)} = \sum_{j \in J} Z_{ij} \tag{3.1}$$

where J represents the set of all vehicle classes. 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:

$$\text{(fatalities imposed on others by class } i\text{)} = \sum_{j \in J} Z_{ji} \tag{3.2}$$

Counts of accidents of each type reflect a combination of factors influencing risk and exposure. I categorize these factors into three multiplicative components, the first two of which can be separately identified in estimation: 1) The risk coming from the behavior of drivers in each vehicle class, 2) risk coming from physical vehicle characteristic alone – I will call this the "engineering" risk, and 3) the number of vehicles in each class present on the road at any given time and place. The combination of these three elements determines the number of fatal accidents in each combination of classes: Intuitively the greater the driver recklessness, engineering risk, or number of vehicles, the more fatal accidents we should expect.

Define the three components using:

α_i The riskiness and safety behavior of the drivers of each vehicle class i (i.e. a separate fixed effect on driver behavior for each class)

β_{ij} The risk of a fatality in vehicle i when vehicles from class i and class j collide (i.e. fixed effects for every possible combination of vehicles)

n_{is} The number of vehicles of class i that are present at time and place s

I define the measure of driver riskiness such that it multiplies the overall fatality risk. For example, a value of $\alpha_i = 2$ will correspond to a doubling of risk. High values of α_i come from a tendency of class i owners to disobey traffic signals, drive when distracted or

drunk, drive recklessly, or take any other action (observable or unobservable) that increases the risk of a fatal accident.

Combining the definition of dangerous driving behavior with the engineering fatality risk results in:

$$\text{Probability of a fatal accident} \mid i, j \text{ present} = \alpha_i \alpha_j \beta_{ij} \tag{3.3}$$

The probability of a fatal accident, conditioned on vehicles *i* and *j* being present at a particular time and place, is modeled as the product of the underlying engineering risk in a collision of that type, β_{ij}, and the parameters representing bad driving, α_i and α_j.

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;[8] such accidents give drivers little time to alter behavior based on attributes of the other vehicle or driver.

Finally I add in the effect of the number of vehicles of each class present in time and place *s*. 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 bin the data 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. In my notation *s* will correspond to bins.

The effect of the quantity of vehicles present in bin *s* on the number fatalities expected again takes a natural multiplicative form: If there are twice as many cars of a certain class on the road then we expect twice as many cars of that class to be involved in an accident:

$$E(Z_{ijs}) = n_{is} n_{js} \alpha_i \alpha_j \beta_{ij} \tag{3.4}$$

[8] NHTSA (2008a).

For this final step we add a bin *s* subscript to the counts Z_{ijs}, keeping track of fatal accidents both by vehicle type and by bin.

Given that the α_i terms include unobservable driving behaviors it is impossible to estimate equation (3.4) alone; it can't be separately determined if a vehicle class is dangerous in a causal engineering sense or if the drivers who select it just happen to drive particularly badly.

The method I propose here separates driver behavior from the underlying safety risk via a second equation describing single-car accidents. I define the count of fatal single-car accidents in vehicle class *i* in location *s* as Y_{is} where:

$$E(Y_{is}) = n_{is}\alpha_i\lambda_s x_i \tag{3.5}$$

The four parameters are:

n_{is}	(As above) The number of vehicles of class *i* present in bin *s*
α_i	(As above) The riskiness of drivers owning vehicles of class *i*
λ_s	A bin-specific fixed effect allowing the overall frequency of fatal single-car accidents to vary freely across time and space.
x_i	The relative fatality risk to occupants of class *i* in a standardized collision (to be measured using government crash tests).

The key restriction across equations (3.4) and (3.5) is that the dangerous behaviors contained in α_i multiply both the risk of single-car accidents and the risk of accidents with other vehicles. This may be a better assumption for some behaviors (drunk driving, recklessness) than others (falling asleep) but I will show below that it appears to fit the data well.

Comparison with other models in the literature

Much of the previous work focusing on the influence of weight of vehicles (see Kahane [2003]) has taken a parametric approach and attempts to isolate the effect of weight

alone. By assigning a complete set of fixed effects for all possible interactions, β_{ij}, I can still recover information about vehicle weight, but add considerable flexibility in form and am able to account for other attributes that vary by class. The cost to my approach comes in terms of demands on the data and the degree of aggregation (I will aggregate to 10 distinct classes, or 100 β_{ij} fixed effects).

Wenzel and Ross (2005) describe overall risks using a similarly flexible approach for vehicle interactions but importantly do not model driving safety behavior, and so are unable to separate it from underlying engineering risk. For purpose of comparison I provide estimates of a restricted version of my model where I set all the α_i 's to be equal. The parameter estimates turn out to be quite different, so much so in fact that the primary policy implication is reversed in sign.

4. Data

This section describes my data sources for each of the variables needed to estimate (3.4) and (3.5):

- Fatal accident counts, Z_{ijs} and Y_{is}
- The quantity (number of vehicle miles) in each class, n_i
- Crash test data to describe risks in single-car accidents with fixed objects, x_i

Fatal accident counts

The count data on fatal accidents represent the core information needed to estimate my model. I rely on the comprehensive Fatal Accident 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 similar framework 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 not only the vehicle class and information about where and when the accident took place (which I use to define bin s in the model), but a host of other factors like weather, and distance to the hospital. While the additional data isn't needed in my main specification (which captures both observed and unobserved driver choices in fixed effects) I will make use of a number of these other values to investigate the robustness of my estimates.

I bin the data 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 s in my central specification. I experiment with adding more bins using other demographics and geography and find that additional detail neither influences the estimates nor adds precision. The robustness of my results to alternative bin structures is included in the sensitivity analysis.

For my main specification I pool data for the three years 2006-2008. I experiment with month fixed effects and a non-overlapping sample of data from 1999-2001 and find no important differences in results. The persistence in the vehicle fleet due to the relatively long life-spans of cars is likely an important factor in the stability of accident rates over time.

Quantity of vehicles present

I use the total vehicle miles traveled (VMT) in each class as a measure of the quantity of vehicles of that class present on the road. This data is available from the National Household Transportation Survey (NHTS), which is a detailed survey of more than 20,000 U.S. households conducted in 2008. While I do have some information about the location of the VMT (for example the home state of the driver) I can't observe other important aspects like the time of day or type of road where the miles are driven. Fortunately, as shown in Section 5, it is possible to recover values for the parameters defining driver behavior using only the total VMT for each class: bin s level VMT is absorbed in fixed effects.

Crash test data

NHTSA has performed safety tests of vehicles using crash-test dummies since the 1970's, 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 available from the crash tests and reflects the probability of a fatality very close to linearly (Herman (2007)). The linearity is important for my application, as I need a measure that reflects the relative risk across vehicle types.

I have assembled the average HIC by vehicle class for high-speed frontal crash tests conducted by NHTSA over the period 1992-2008.[9] These tests are meant to simulate typical high-speed collisions with fixed objects (such as concrete barriers, posts, guardrails, and trees) that are common in many fatal single-car accidents. The values for each class are included in Table 1. 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.

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 the sensitivity analysis that abstracts altogether from crash-test data. It produces quite similar results but offers less precision since it places more burden on cross-equation restrictions.

Summary statistics

I define 10 vehicle types (classes) spanning the range of the U.S. passenger fleet, including various sizes of cars, trucks, SUV's, and minivans. Table 1 provides a list and a summary of the accident counts, reflecting fatalities both in the vehicle and those of other drivers in accidents. The quantity data is summarized in column 3, displaying the total annual miles traveled in each class. Finally, I include the HIC data for each class, representing the relative risks of a fatality in single-car crashes.

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

Table 2 describes the data on fatal accidents, broken down by bin *s*. The first three columns indicate total fatal accidents in my sample, summarizing 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 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 the accident rates in all 100 possible combinations of classes is provided in Table 3, and is discussed in detail in the following section.

5. Estimation and Results

The equations from Section 3 representing single and multi-car accidents respectively are:

$$E(Y_{is}) = n_{is}\alpha_i\lambda_s x_i \tag{5.1}$$

$$E(Z_{ijs}) = n_{is}n_{js}\alpha_i\alpha_j\beta_{ij} \tag{5.2}$$

Since the parameters for driving behavior and quantity are only relevant up to a constant (they expresses relative riskiness and vehicle density, respectively) I combine them into a single term for estimation: $\delta_{is} \equiv n_{is}\alpha_i$ and normalize the first δ_{is} to unity. The average risks by class α_i can be recovered after estimation using the aggregate data on miles traveled.[10]

[10] In particular, define n_i as the aggregate quantity (miles) for class *i* such that $n_i = \sum_s n_{is}$. Then $\sum_s \delta_{is} \big/ n_i = \sum_s n_{is}\alpha_i \big/ n_i = \alpha_i$.

The transformed model for estimation is:

$$\begin{aligned} &Y_{is} \sim \text{Poisson}(\omega_{is}) \\ &E(Y_{is}) = \omega_{is} = \delta_{is}\lambda_s x_i \end{aligned} \tag{5.3}$$

$$\begin{aligned} &Z_{ijs} \sim \text{Poisson}(\mu_{ijs}) \\ &E(Z_{ijs}) = \mu_{ijs} = \delta_{is}\delta_{js}\beta_{ij} \end{aligned} \tag{5.4}$$

where x_i and the realizations of Y_{is} and Z_{ijs} are data. All remaining parameters are to be estimated and require simultaneous estimation of the two equations for identification. For convenience in programming, the data is transformed by natural logs and fit using the maximum likelihood command in the Stata 11 package. All coefficients and standard errors in the tables below are reported in exponentiated form, such that they can be interpreted directly as the multiplicative terms appearing in my model.

Overdispersion in count data is often present, and can be captured by modeling the negative binomial generalization of the Poisson distribution. The negative binomial distribution includes one additional parameter, similar to estimating the variance of an error term in a linear model, and reduces to the Poisson distribution as overdispersion falls to zero. My point estimates remain virtually unchanged relative to the simple Poisson model, with a slight increase in standard errors. In all results below I report estimates from the more general negative binomial version of the model.

Identification

The separate identification of α_i and β_{ij} comes from the cross equation restrictions above, but it may be useful to provide some additional intuition:

Consider a simplified version of (5.3) abstracting from the λ_s fixed effects: We would have simply $\omega_{is} = \delta_{is}x_i$. The unknown parameters here are just the δ_{is}'s which can be exactly identified using the counts of single-vehicle accidents and crash test data. Effectively, I measure the quantity of dangerously driven vehicles of each class by seeing how many single-car fatalities occur and adjusting for the riskiness of the vehicle involved.

Once the δ_{is} 's are known the remaining parameters in (5.4) are just the β_{ij} 's, which are now straightforward to recover separately.

In practice of course the fixed effects for single-car accidents are also very important (certain types of roads and times of day are much more conducive to single-car accidents). Intuitively, these can be identified using the additional observations in the second equation (since there are *s* pieces of data over-identifying each β_{ij} parameter).

Results from a restricted model

For purpose of comparison I first estimate a restricted model where I combine driving behavior and underlying engineering safety into a single parameter. The next subsection displays the full model, where the effects are separated.

For the restricted model I retain the full set of fixed effects on bins *s* and vehicle interactions β_{ij} but drop the terms for driver behavior:

$$\begin{aligned} &Z_{ijs} \sim \text{Poisson}(\tilde{\mu}_{ijs}) \\ &E(Z_{ijs}) = \tilde{\mu}_{ijs} = \tilde{n}_{is}\tilde{n}_{js}\tilde{\beta}_{ij} \end{aligned} \tag{5.5}$$

where the parameters are defined as before, and the ~ modifier indicates the restricted model.

Table 3 presents the restricted estimates of $\tilde{\beta}_{ij}$. The parameters have a simple interpretation: they are the total fatality rates in interactions between each pair of classes. The most dangerous interaction in the table occurs when a compact car collides with a large pickup truck, resulting in 38.1 fatalities in the compact car per billion miles that the two vehicles are driven. The chance of a fatality in the compact in this case is about 3 times greater than if it had collided with another compact, and twice as large as if it collided with a full-size sedan. What is omitted from this table is the possibility that some classes contain more fatalities due to dangerous driving, rather than because of any inherent risk.

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 below that this is resolved by allowing flexibility in driving behavior; minivans tend to be driven much more safely.

Results from the full model

By estimating 5.3 and 5.4 simultaneously my full model is able to separate the accident rates shown in Table 3 into two pieces: The portion attributable to driver behavior, and the portion that comes from the physical characteristics of the vehicles themselves. The semi-parametric form allows me to be agnostic about which physical attributes of the vehicles cause the changes in underlying safety; the influence of any characteristic of interest (for example vehicle weight) can be easily calculated *ex post* from my full matrix of estimates.

My central estimates appear in Table 4. The first row displays estimates of α_i, or the driving safety risks (from both observed and unobserved factors) among people who select vehicles in each of the ten groups. Average safety is normalized to unity and standard errors appear in parentheses. For easier comparison, I also display 95% confidence intervals graphically in Figure 1. I find that minivan drivers are the safest among all classes, with accident risks that are approximately 1/3 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 SUV's tend to be driven in urban areas (which are much safer than rural areas in terms of fatal car accidents) and are among the more expensive vehicles. Pickup trucks are driven significantly more dangerously than SUV's of similar sizes, also intuitive given their younger drivers and prevalence in rural areas. 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 underlying safety across all vehicle interactions. The fatality rates shown are per billion miles, and now represent a

situation where driving behavior is fixed at the average in both vehicles: i.e. a standardized collision with only the physical attributes of the two vehicles allowed to vary. Fatalities occur in the vehicle indicated in the row and the externality imposed by the larger classes on the smaller ones is evident. The largest risk occurs in a compact car when it is struck by a large pickup.

A number of key differences in β_{ij} appear relative to the summary of accident rates shown in Table 3: without including differences in driving behavior large pickup trucks appear much more dangerous to other drivers than large SUV's (compare columns 7 and 9 of Table 3). After correcting for driving safety, the two classes of vehicles now appear very similar (columns 7 and 9 of Table 4). This is an intuitive result in terms of physical attributes: Large SUV's and large pickups have similar weight and size, often being built on an identical light truck platform. Minivans now also look like the light trucks that they are based on (in fact 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.

β_{ij} and the effects of vehicle weight

While I wish to focus on the policy implications of driver behavior combined with engineering safety, a closer examination of the engineering coefficients in isolation is useful to test the plausibility of my results and relate them to the literature: Much of the related work in engineering and economics has focused on the physical effect of vehicle weight on accident fatalities, controlling away driver behavior. In particular, there has been interest in both the protection that vehicle weight offers as well as the externality that it imposes on others. Both of these quantities can be calculated from my estimates of β, but will necessarily be rough measures due to aggregation.

Weighted averages of the columns in Table 4 provide a measure of the external effect; that is, the average number of fatalities that each class imposes on the other vehicle involved in an accident after driver behavior has been removed. I fit the following line, relating weight in each class to the natural log of external fatality risk:

$$\ln\left(\frac{\sum_i n_i \beta_{ij}}{\sum_i n_i}\right) = a + b \cdot weight_i \tag{5.6}$$

where $weight_i$ is an average measured in thousands of pounds for each class i. The least squares estimate of b is 0.46, suggesting that 1000 pounds of weight increases the number of fatalities in other vehicles by 46%. The protective effect of weight can be similarly calculated (averaging the rows of Table 4), and the slope coefficient suggests each 1000 pounds of vehicle weight reduces own risk by 54%.

Evans (2001) estimates both the external and internal effects of vehicle weight using differences in the number of occupants in the striking and struck car. This strategy helps avoid a host of selection issues, since it allows weight to vary holding all other attributes of the vehicle fixed. He finds that 1000 pounds increases external risk by 42% and decreases own risk by 40%.[11] Kahane (2003) focuses on own safety risk: for passenger cars the central estimate of the protective effect is 44% per 1000 pounds of weight.[12] Kahane's estimates for light trucks, in contrast, are not robust and vary between -30% and +70% depending on accident type and vehicle size. Kahane speculates in his report 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 light trucks are much stronger than those among passenger cars.

Anderson and Auffhammer (2011) also wish to isolate the effects of weight, and carefully control for accident and driver characteristics. They argue that conditioning on accident occurrence (either fatal or not) controls for most of the driver selection, such that the remaining fatality risk can be attributed to the physical characteristics of the vehicle. They find that 1000 pounds of weight increases external risk by 47%. The rough estimate of the weight externality contained in my β_{ij} parameters is very similar. At least along the

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[11] In particular, they estimate that each adult occupant adds 190 pounds on average and that striking vehicles with an extra adult occupant increase the fatality risk in the other car by 8.1%.

[12] The report includes a very 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.

dimension of vehicle weight, this suggests that the multiplicative structure I impose in equations (3.4) and (3.5) has not restricted the underlying pattern in the data.

6. Policy Simulations

An economic analysis of safety and fleet composition turns on two sets of parameters: The underlying engineering causes of fatal accidents, and the behavior of the individuals who drive the different vehicle types. I recover both sets of estimates in the framework above. In this section I return to the motivating policy question and demonstrate the use of my estimates in analyzing the fleet composition effects associated with different types of fuel economy standards.

I will make two key assumptions in order to conduct the simulations: i) I parameterize the types of switching induced by fuel economy standards (e.g. more small SUV's in place of large SUV's) and ii) I assume that the behavior of drivers moves with them as they switch vehicles. For (i) I compute shadow costs and draw substitution elasticities from the literature, detailed below.

Assumption (ii), fixing the behavior of drivers as they switch vehicles, is by nature an approximation: at the margin, some driving behaviors will change as people switch from one vehicle to another.[13] However, I argue that the most powerful baseline indicators of driver risk are likely to stay with the driver as they switch vehicles: these include income, alcohol use, age, gender, education, and location in a rural area. My simulations therefore present one bound, where driver behavior remains the same. The other bound could be constructed by assuming that individuals adopt the unobserved characteristics common to drivers of the vehicle they switch into.

Finally, the farther out of sample I wish to look in simulation (i.e. very extreme changes to the fleet) the more strain is placed on the empirical estimates. Fortunately, there is a substantial amount of variation in the fleet already included in the data: For example the fraction of the fleet that are large pickup trucks varies by more than factor of two across bins

[13] As in Peltzman (1975).

s.[14] The changes as the result of fuel economy rules span only a small piece of this variation.

Simulation Model

I begin with a set of estimates for own and cross-price elasticities of demand among the 10 vehicle classes. The central-case elasticities I use are shown in Table 5 and come from Bento et al (2009). To determine the change in fleet composition I combine the matrix of elasticities with the shadow tax implicit in fuel economy regulation.[15] The shadow taxes are displayed in Table 6 for each of the three policies I consider:

1) Extension of the current CAFE rule

The shadow tax in this case is proportional to fuel economy within the light truck fleet and within the car fleet. This means that large pickups receive a shadow tax while small pickups receive a shadow subsidy. Similarly large cars receive a shadow tax while compacts receive a shadow subsidy. There is no incentive to switch from trucks and SUV's into cars with this policy, since they are regulated by separate average requirements.

2) Single standard

Here the shadow tax is very simple: The least efficient vehicles receive the highest tax and the most efficient ones the highest subsidy. All are in proportion to fuel economy. In general trucks receive a shadow tax (the worse their fuel economy the more so) and cars receive a shadow subsidy.

3) Footprint-based CAFE standard

This more complicated policy targets fuel economy for vehicles based on their wheelbase and width. Large footprint vehicles are given a more lenient target, leaving little or no incentive for manufacturers to change the composition of vehicle types they produce.

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[14] It ranges from 10% (high-income, urban, daytime) to 22% (low-income, rural, night).
[15] Average fuel economy regulation places a shadow tax on vehicles that fall below the average requirement and a shadow subsidy on vehicles that are more efficient than the requirement.

The only residual effect on fleet composition will be for classes that are either particularly efficient relative to their footprint (non-luxury cars) or particularly inefficient relative to their footprint (SUV's).

Combining the matrix of elasticities with the regulatory shadow taxes allows me to both calculate the new composition of the fleet and also track the types of drivers as they switch across vehicles. Accident rates can then be updated by combining driver risk and the risks inherent in the engineering characteristics of the changed vehicle fleet.

For example: If the policy causes a lot of large-pickup drivers to now buy small SUV's instead, I would predict that the average driving safety behavior in small SUV's worsens: The small SUV class will now contain the relatively safe, urban drivers it originally included, and now also add some drivers from the more dangerous category that formerly owned large pickups. This change in average driver behavior is combined with the underlying engineering risk in the vehicles.

More formally, I compute the updated driver behavior, $\hat{\alpha}_i$, by taking a quantity-weighted average of the safety characteristics of drivers from all the classes who have switched into class *i* as a result of policy. This is combined with those who choose class *i* both before and after the regulation. The predicted number of fatalities under the new policy scenarios is given by:

$$\hat{Z}_{ijs} = \hat{n}_{is}\hat{n}_{js}\hat{\alpha}_i\hat{\alpha}_j\beta_{ij} \tag{6.1}$$

$$\hat{Y}_{is} = \hat{n}_{is}\hat{\alpha}_i\lambda_s x_i \tag{6.2}$$

where $\hat{\alpha}_i$ is the new driver safety value as above and $\hat{n}_i$ reflects the new fleet composition induced by the policy.

Simplifying assumptions

In order to keep the analysis tractable I abstract from issues of scale and accidents outside the passenger fleet as follows:

i) *Commercial vehicles*: I assume that the fleet of commercial vehicles (mainly heavy trucks for which a commercial driver's license is required) remains fixed. I leave the number of fatalities occurring in commercial vehicles unchanged, and adjust the fatalities in passenger vehicles that collide with commercial vehicles using the same risk factors I estimate for single-car accidents.[16]

ii) *The scale of the fleet and miles driven*: It may be that fuel economy rules will change the total number of cars sold (likely decreasing it) or the number of miles driven (likely increasing that).[17] I abstract from these effects altogether, holding the total number of vehicles and miles driven constant. This allows me to focus on the influence of composition alone.

iii) *Pedestrians and cyclists*: About 12% of fatalities involving passenger vehicles are pedestrians, bicyclists, and motorcyclists. Pedestrian and cyclist fatality rates (uncorrected for driver behavior) are nearly identical among cars and light trucks, consistent with the observation that the mass of the passenger vehicle is many times larger regardless of its class.[18] I therefore assume a constant rate of fatal accidents involving pedestrians. To the extent that smaller vehicles could reduce pedestrian fatalities – for example because of better visibility when reversing – both the uncorrected and corrected results in my model would change by the same amount: The divergence in estimates I find when accounting for driver behavior would be unaffected.

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[16] This is a reasonable approximation since the much larger mass of commercial trucks means collisions with them resemble collisions with fixed objects (albeit at very high speed if the collision occurs head-on).

[17] A decrease in quantity might come from cost increases as fuel-saving technologies are introduced. An increase in miles is known as the rebound-effect; better fuel economy means driving becomes cheaper at the margin.

[18] Pedestrian and cyclist 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 higher for larger vehicles. Surprisingly, the opposite effect holds within cars: larger vehicles have lower pedestrian fatality rates.

Results of policy simulations

The results of the three policy simulations are contained in Tables 7 through 9. I provide standard errors for the total change in fatalities in each case by applying the delta method. The standard errors reflect the estimates of the safety parameters made in this paper; the hypothetical changes in fleet composition are treated as deterministic.

1) Increment of 1.0 MPG to the current CAFE rules:

The left panel of Table 7 displays the change in total traffic deaths that are predicted using the restricted model, where driving behavior is not estimated. This restricted model suggests that CAFE offers an improvement in safety: 135 lives would be saved.

A very different picture emerges when I use the full model, modeling the selection on driving behavior at the class level. The central estimate is that the increment to CAFE will result in 149 additional traffic-related fatalities per year.

It is straightforward to see the intuition behind the reversal in sign: Large SUV's and pickups (and large sedans) cause and experience a lot of fatal accidents in the data. The naive 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. When we move those people into smaller vehicles it does not diminish the risk, and in some cases can even magnify it since smaller vehicles do more poorly in most single-car accidents.

It is important to point out that the effects I'm finding are not all habits that we would fault the drivers themselves for (like running through traffic signals). A significant portion is simply the urban-rural divide: Drivers who currently choose large vehicles tend to live in rural areas, where accident fatality rates are very high. As rural drivers change to smaller vehicles the dangers of accidents on rural highways remain. These are very often single-car accidents, as reflected in the composition of additional fatalities I predict.

2) Unified standard achieving a 1.0 MPG improvement

Table 8 presents results under a unified standard, which has a strikingly different effect from an increment to current CAFE rules. My full model shows an increase of only 8 fatalities per year under a unified standard. A zero change lies within the confidence bounds. This represents a highly statistically significant improvement over an increment to current CAFE and comes as the result of two effects canceling each other out in the fleet:

The first effect reiterates the undesirable outcome in the first experiment, that is, changes within the car fleet and within the truck fleet lead to smaller and lighter vehicles and increase the number of fatalities.

Recall though that the unified standard adds a second incentive: It encourages switching away from light trucks and SUV's and into cars. I estimate that this second effect improves overall safety substantially. There appears to be something about light trucks (likely the height of their center of mass) that makes them more dangerous vehicles than cars, even after controlling for their drivers. Exchanging an average truck for an average car confers a large safety benefit to the fleet. It turns out that this improvement almost exactly offsets the deterioration of safety within the car and truck fleets due to the down-sizing of vehicles.

3) Footprint-based standard

Table 9 presents results under the footprint-based standard that is in effect until 2016. The footprint-based standard discourages most types of composition changes by shutting down switching both within and across the car and truck fleets. The most significant changes that remain are movement away from SUV's and into pickup trucks and cars; this is due to the relatively small footprint of SUV's relative to their fuel consumption. My full model shows a very small deterioration in safety from the footprint standard, with an increase of only 6 fatalities per year.

It is important to point out that these small safety effects come paired with large efficiency costs: Fuel savings under the footprint standard must be accomplished almost

exclusively through engine technology, when movement to a smaller and lighter fleet is likely to be a much cheaper way to save gasoline.

My results on the unified standard 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. As the U.S. presses toward even more fuel efficiency after 2016, changes in fleet composition will prove valuable and can be made with safety consequences fully in mind.

7. Alternative Models

Estimating driver behavior without using crash test data

It is possible to identify my empirical model (including the measurement of driver behavior by class) without the use of crash test data, relying instead on the physical properties of accidents: Accidents between two vehicles of similar mass and speed closely resemble accidents with fixed objects since both crashes result in rapid deceleration to a stationary position.[19] When vehicles of different mass collide, the heavier vehicle will decelerate more slowly (pushing the smaller vehicle back) which creates asymmetry in the degree of injuries.

My alternative identification strategy makes use of this property, setting risk in single car accidents proportional to the risk in accidents between cars of the same class, β_{ii}. The model described in Section 5 becomes:

$$E(Y_{is}) = n_{is}\alpha_i\lambda_s\beta_{ii} \tag{7.1}$$

$$E(Z_{ijs}) = n_{is}n_{js}\alpha_i\alpha_j\beta_{ij} \tag{7.2}$$

The restriction on the diagonal elements of β is sufficient for identification.

[19] See Greene (2009). Each vehicle's change in velocity raised to the 4th power closely predicts injury severity.

The first two columns of Table 10 provide a summary of results from my preferred specification in Section 5. The third column shows the results from estimating (7.1) and (7.2) above, providing a confirmation of the central findings even under very different identifying assumptions. The standard errors are much larger in this specification, reflecting the reduction in data available to the model.

Alternative demand elasticities

The general pattern in the simulation, that fewer large vehicles and more small ones will be sold, is fundamental to a reduction in fuel economy. However, my simulation also embeds more subtle changes in substitution across classes. For example: Is a driver giving up a large SUV more likely to buy a small SUV or switch to a small pickup truck?

I investigate the robustness of my simulation results by introducing an entirely separate set of substitution elasticities, shown in Table 11. These are reported in Kleit (2004) and are also employed by Austin and Dinan in their 2007 work. The elasticities derive mainly from survey data on second-choices of new car owners, providing a different view than the cross-sectional variation used to generate the elasticities in my main simulation.

The fourth column of Table 10 summarizes the results under the alternative elasticities. My main findings remain intact, though the effectiveness of a single fuel economy standard at mitigating safety consequences is somewhat muted relative to my preferred model.

Additional robustness checks

I also investigate the robustness of my findings in a number of subsamples of the data. Columns 3 through 5 of Table 12 summarize my main results in various subsamples, with total fatalities scaled by the number of observations used so that the columns are comparable.

1998 and newer model years

1998 was the first model year where both passenger and driver airbags were required in all new vehicles. Airbags dramatically alter safety risks, and if their presence also influences driving behavior or changes relative risks across classes we might expect a different set of results to emerge. My estimates, however, appear robust in this dimension.

Drivers under 55

There is evidence that elderly drivers may more often be the subjects of fatal traffic accidents due to their relative frailty.[20] This introduces a potential asymmetry in my model: Older drivers may place themselves at greater risk but don't necessarily impose this risk on those around them. I restrict my sample to driver fatalities among those less than 55 years old and find similar results, suggesting that the frailty effect is not large relative to the variation in driver behavior overall.

Clear weather

My simulations assume that the locational or behavioral factors influencing driver safety remain with the driver after the change in composition. A potentially important caveat has to do with weather: If a driver switches away from an SUV, for example, they may be less likely to drive in the rain or snow. I therefore experiment with a sample limited to fatalities that occur in clear weather (any weather condition, even fog or mist, is excluded). Notably, this only removes 10% of observations; 90% of fatal accidents occur in clear conditions. My results are again unchanged, suggesting that even if there is substantial behavioral response to weather conditions it would not be relevant to most accident fatalities.

8. Conclusion

I introduce a new empirical model of vehicle accidents that provides estimates of both the behavior of drivers and the underlying risk associated with engineering

[20] Loughran and Seabury (2007) investigate this issue.

characteristics in a single framework. To my knowledge this is the first study to capture unobserved driver behavior (as fixed effects) and the impact of physical vehicle characteristics simultaneously. I show that correctly accounting for both factors in accidents significantly alters conclusions about fleet composition and safety.

Two main effects 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 interactions between vehicles that closely mirrors theoretical engineering results. Large and heavy vehicles are the safest to be in during an accident but also cause the most external damage to others. When reduced to the single dimension of vehicle weight, my estimates of the own and external effects of heavier vehicles match those in the literature closely.

I also address directly the motivating question relating safety and fuel economy regulation. I find that the provision in existing CAFE regulation to separate light trucks and SUVs from passenger cars is harmful to safety: Incrementing the standards by 1.0 mile per gallon 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 any additional injuries or property damage (assuming they are correlated with fatalities) further increasing the cost of this type of regulation.[21] 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. Using the same argument above, a unified standard neither increases nor decreases the diversity in the fleet. The additional fatalities incurred by switching to smaller and lighter cars and trucks are offset almost exactly by switches between the two categories.

[21] The gasoline savings here reflect only fleet composition changes, holding miles driven fixed. To the extent that a "rebound effect" increases miles driven, the safety cost per gallon saved would be even larger.

Further analysis using the model developed here could uncover additional effects of interest. For example, a more detailed disaggregation of car classes by manufacturer, fuel economy, or other attribute could reveal additional ways to adjust fuel economy rules to protect or even improve safety. The policy simulations might similarly be made richer, with attention given to inter-firm dynamics or the credit-trading provisions in upcoming federal regulation.

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Table 1: Summary Statistics by Class

Class	Count of Accident Fatalities[1] Own Vehicle	Count of Accident Fatalities[1] Other Vehicle	Total Miles Driven[2]	Crash Test HIC[3]
Compact	2812	1068	247.7	528.7
Midsize	2155	1280	249.7	491.4
Fullsize	733	507	83.2	353.9
Small Luxury	317	236	54.5	424.3
Large Luxury	364	307	50.8	469.3
Small SUV	719	1129	216.0	626.3
Large SUV	477	1379	148.9	531.2
Small Pickup	594	624	87.1	666.2
Large Pickup	716	2293	159.5	585.9
Minivan	469	532	126.7	577.9

[1] Two-car accidents, annual average 2006-2008.
[2] In billions of miles per year (2008 National Household Transportation Survey).
[3] Results from NHTSA testing 1992-2008.

Table 2: Summary Statistics by Bin *s*

Density[1]	Income[1]	Time of Day	Fatalities (1 and 2 Car Accidents) 2006	2007	2008	Variance (Weekly)	Fraction 1-Car	Fraction Light Trucks	Greatest Relative Frequency[2] 1-Car Accidents	2-Car Accidents
Rural	Low	Night	705	673	582	3.92	0.882	0.557	Lg Pickup	Fullsize/Fullsize
		Evening	374	373	320	2.77	0.718	0.485	Lg Pickup	Fullsize/Fullsize
		Day	1574	1475	1310	6.66	0.643	0.519	Lg Pickup	Sm Pickup/Lg Pickup
	Medium	Night	501	518	414	3.47	0.883	0.537	Lg Pickup	Compact/Lg Lux
		Evening	254	257	210	2.16	0.756	0.535	Sm Pickup	Fullsize/Fullsize
		Day	1022	1003	897	4.97	0.585	0.498	Sm Pickup	Sm Pickup/Lg Pickup
	High	Night	341	308	266	2.71	0.897	0.460	Lg Pickup	Sm Lux/Sm Pickup
		Evening	150	133	144	1.65	0.728	0.478	Sm Pickup	Lg Lux/Lg Lux
		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
		Evening	283	265	222	2.37	0.655	0.491	Lg Pickup	Sm Lux/Sm Lux
		Day	1133	1062	953	4.91	0.609	0.528	Lg Pickup	Sm Pickup/Lg Pickup
	Medium	Night	1038	995	946	4.83	0.822	0.491	Lg Pickup	Lg Lux/Lg Lux
		Evening	478	437	368	2.95	0.652	0.471	Lg Pickup	Lg Lux/Lg Pickup
		Day	1850	1671	1569	6.72	0.571	0.473	Lg Pickup	Compact/Lg Pickup
	High	Night	4234	4085	3565	11.96	0.766	0.380	Sm Lux	Compact/Sm Lux
		Evening	1490	1404	1229	5.96	0.599	0.385	Sm Lux	Compact/Lg Pickup
		Day	5786	5525	4801	14.16	0.511	0.386	Compact	Compact/Lg Pickup
All			22439	21399	18868	41.85	0.650	0.441	Lg Pickup	Compact/Lg Pickup

[1] Zip-code level accident fatalities categorized using data from the U.S. Census.
[2] Relative frequencies are calculated as accident counts within group divided by total miles traveled at the national level. A combination of vehicle popularity and driver behavior within group determines the accident with greatest relative frequency.

Table 3: Estimates of $\tilde{\beta}_{ij}$ in Restricted Model (No class-level driver safety effects)[1]

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

[1] Standard errors are shown in parentheses, estimates are from negative binomial estimation of the multi-car accident equation alone, with all class-level safety effects restricted to unity.

Table 4: Central Estimation Results[1]

	Compact	Midsize	Fullsize	Small Luxury	Large Luxury	Small SUV	Large SUV	Small Pickup	Large Pickup	Minivan
α_i: Driver Safety Behavior	1.14 (0.06)	0.98 (0.06)	1.25 (0.08)	1.19 (0.08)	1.05 (0.07)	0.65 (0.04)	1.06 (0.06)	1.09 (0.07)	1.45 (0.08)	0.39 (0.02)
β_{ij}: Fatality rate in vehicle *i*										
Compact	5.8 (0.7)	8.1 (1.0)	7.7 (1.0)	5.1 (0.7)	8.3 (1.1)	13.3 (1.6)	13.3 (1.6)	10.9 (1.4)	16.3 (1.9)	16.7 (2.1)
Midsize	4.8 (0.6)	7.4 (0.9)	6.5 (0.9)	4.4 (0.7)	7.2 (1.0)	10.6 (1.3)	11.8 (1.4)	10.1 (1.3)	14.9 (1.8)	14.1 (1.9)
Fullsize	3.8 (0.5)	5.9 (0.8)	6.3 (1.0)	3.5 (0.7)	6.7 (1.2)	8.7 (1.2)	8.7 (1.2)	8.4 (1.2)	11.7 (1.5)	12.2 (1.9)
Small Luxury	3.4 (0.5)	3.1 (0.5)	4.4 (0.8)	3.8 (0.8)	4.5 (1.0)	7.1 (1.1)	5.5 (0.9)	3.5 (0.7)	6.8 (1.0)	6.4 (1.3)
Large Luxury	3.2 (0.5)	4.9 (0.7)	5.2 (1.0)	2.5 (0.7)	5.6 (1.3)	8.7 (1.3)	10.7 (1.5)	7.5 (1.3)	10.4 (1.4)	11.7 (2.2)
Small SUV	2.9 (0.4)	4.0 (0.5)	3.4 (0.6)	3.1 (0.6)	5.8 (1.0)	6.1 (0.8)	6.8 (0.9)	4.5 (0.7)	8.9 (1.1)	7.9 (1.3)
Large SUV	2.1 (0.3)	2.4 (0.3)	1.7 (0.3)	1.7 (0.4)	2.7 (0.5)	3.1 (0.5)	4.2 (0.6)	3.0 (0.5)	4.9 (0.6)	5.3 (0.9)
Small Pickup	4.4 (0.6)	5.2 (0.7)	4.8 (0.8)	2.4 (0.6)	3.7 (0.8)	6.8 (1.0)	7.8 (1.1)	7.4 (1.2)	13.0 (1.6)	11.6 (1.9)
Large Pickup	2.1 (0.3)	2.6 (0.3)	2.2 (0.4)	1.8 (0.4)	2.8 (0.5)	3.2 (0.5)	4.4 (0.6)	3.3 (0.5)	7.4 (0.9)	4.3 (0.7)
Minivan	4.9 (0.7)	6.0 (0.9)	7.6 (1.3)	4.4 (1.0)	5.5 (1.3)	11.8 (1.7)	12.7 (1.8)	11.6 (1.9)	17.3 (2.3)	18.2 (3.1)

Negative binomial regression
Number of obs: 308880
Log likelihood: -89321
Wald chi2(297): 233212

[1] Estimates of α_i reflect driver safety risks by class, normalized so that a value of unity represents the average driver overall. β_{ij} are estimated rates of fatalities in car *i* (row) when colliding with car *j* (column) after removing differences in driver behavior. Standard errors are in parentheses; all coefficients are different from 0 at the 5% level.

Table 5: Matrix of Demand Elasticities by Class

	Compact	Midsize	Fullsize	Small Luxury	Large Luxury	Small SUV	Large SUV	Small Pickup	Large Pickup	Minivan
Compact	-3.51	0.97	0.42	0.32	0.21	0.67	0.49	0.41	0.51	0.52
Midsize	0.80	-3.01	0.31	0.16	0.15	0.41	0.31	0.32	0.32	0.29
Fullsize	0.79	0.73	-4.94	0.14	0.21	0.31	0.44	0.30	0.45	0.30
Small Luxury	0.59	0.35	0.14	-5.15	0.15	0.46	0.16	0.13	0.24	0.16
Large Luxury	0.42	0.36	0.22	0.16	-4.18	0.24	0.22	0.10	0.21	0.12
Small SUV	0.76	0.54	0.19	0.28	0.14	-2.39	0.25	0.19	0.30	0.29
Large SUV	0.62	0.48	0.31	0.11	0.15	0.27	-2.95	0.19	0.37	0.21
Small Pickup	0.68	0.66	0.26	0.12	0.08	0.29	0.24	-3.96	0.23	0.18
Large Pickup	0.92	0.68	0.44	0.24	0.19	0.48	0.51	0.25	-2.81	0.43
Minivan	0.69	0.47	0.23	0.12	0.08	0.34	0.23	0.15	0.32	-3.31

Table 6: Average Fuel Economies and Shadow Taxes by Class

		Shadow Tax of Policy Increment		
Class	Fuel Economy (MPG)	Increase current CAFE	Unified standard	Footprint CAFE
Compact	31.0	0.28	0.22	0.06
Midsize	27.7	-0.09	0.12	0.05
Fullsize	25.5	-0.31	0.06	0.06
Small Luxury	25.9	-0.22	0.08	-0.02
Large Luxury	23.8	-0.56	-0.01	0.00
Small SUV	24.9	0.37	0.01	-0.11
Large SUV	19.5	-0.44	-0.28	-0.14
Small Pickup	22.6	0.16	-0.07	0.02
Large Pickup	18.6	-0.41	-0.27	0.01
Minivan	23.5	0.29	-0.02	0.06

Table 7: Effect of an Increase in Current CAFE Rules on Total Traffic Deaths

	No driver effects[1]			*Full model*[2]		
	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			(6.1)			(9.4)

[1] This case reflects the restricted model, where driving safety behavior is assumed constant across all classes. Only the quantity of cars of each class changes.
[2] Here the full model is used to predict changes in safety, including the parameters that account for differences in driving safety behavior across classes.

Table 8: Effect of a Unified Fuel Economy Standard on Total Traffic Deaths

	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			(3.8)			(4.3)

Table 9: Effect of a Footprint Fuel Economy Standard on Total Traffic Deaths

	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			(1.3)			(1.5)

Table 10: Alternative Identification Strategy and Alternative Simulation Elasticities

	No driver effects	Full model (central)	Alternative identification	Alternative elasticities
Current CAFE within fleet	-135.02 (6.15)	149.47 (9.36)	222.00 (53.97)	156.15 (10.38)
Trading between cars and trucks	-12.14 (3.81)	8.50 (4.35)	7.31 (21.11)	32.97 (2.85)
Footprint fleet effects	26.88 (1.28)	6.27 (1.52)	-47.55 (5.72)	8.18 (1.27)

Table 11: Alternative Demand Elasticities by Class[1]

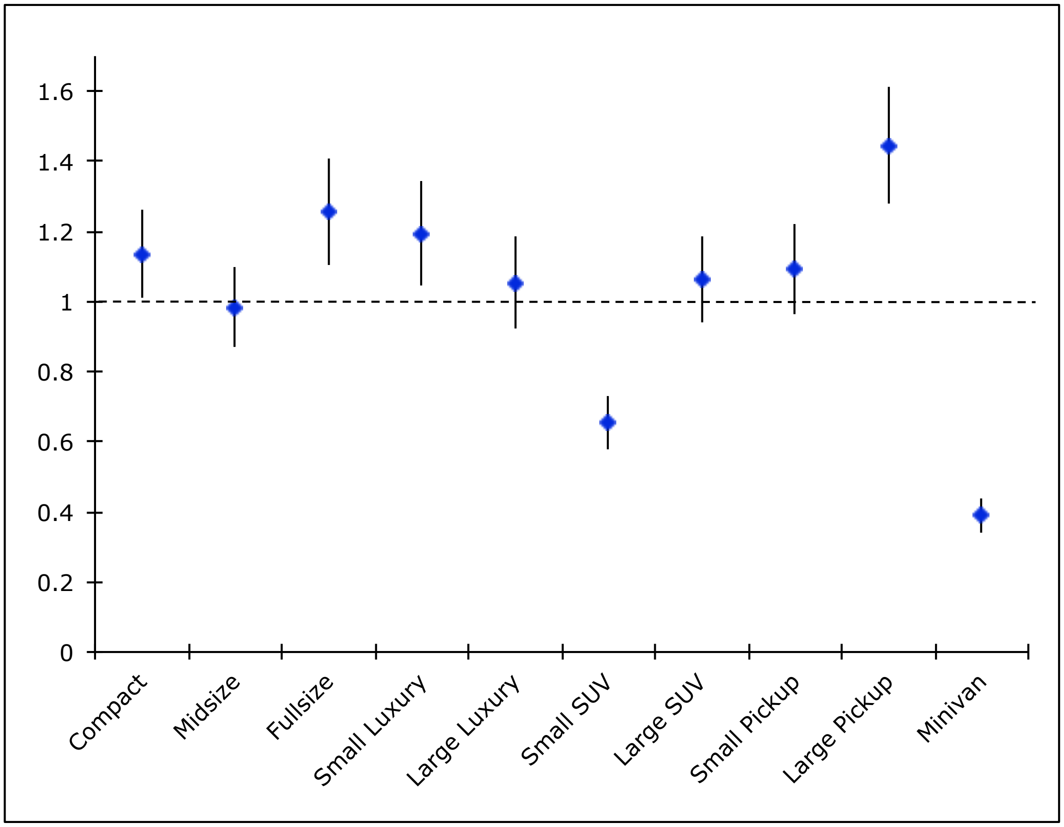
	Compact	Midsize	Fullsize	Small Luxury	Large Luxury	Small SUV	Large SUV	Small Pickup	Large Pickup	Minivan
Compact	-3.12	0.94	0.06	0.10	0.00	0.10	0.01	0.12	0.03	0.03
Midsize	1.64	-3.92	1.10	0.15	0.06	0.39	0.07	0.06	0.02	0.19
Fullsize	0.65	4.28	-5.00	0.15	0.75	0.20	0.09	0.03	0.07	0.19
Small Luxury	1.32	0.94	0.32	-2.50	0.03	0.49	0.12	0.31	0.25	0.06
Large Luxury	0.11	0.90	1.06	0.05	-1.93	0.49	0.23	0.00	0.03	0.25
Small SUV	0.52	0.62	0.10	0.15	0.03	-4.05	0.96	0.31	0.44	0.38
Large SUV	0.24	0.45	0.14	0.09	0.05	3.73	-2.29	0.16	0.40	0.93
Small Pickup	0.39	0.22	0.00	0.05	0.00	0.49	0.08	-3.32	0.88	0.03
Large Pickup	0.15	0.16	0.02	0.05	0.00	0.30	0.16	0.81	-1.72	0.06
Minivan	0.19	0.38	0.06	0.00	0.03	0.30	0.46	0.03	0.06	-2.54

[1]Elasticities from Kleit (2004) aggregated to match the ten class definitions in my model. In order to isolate the effects of fleet composition I also proportionally adjust the cross-price elasticities such that fleet size is exactly maintained.

Table 12: Additional Robustness Checks

	No driver effects	Full model (central)	1998 and newer	Drivers under 55	Clear weather
Current CAFE within fleet	-135.02	149.47	142.15	132.82	148.52
Trading between cars and trucks	-12.14	8.50	6.27	-2.47	8.26
Footprint fleet effects	26.88	6.27	0.56	3.36	6.99
Fraction of accidents		1.00	0.52	0.77	0.90

Figure 1: Estimates of α_i in Full Model[1]



[1] Values are taken from the first row of Table 4 and bars indicate 95% confidence intervals. The average driving safety behavior is normalized to 1.