PRELIMINARY DRAFT

Fuel Economy, Car Class Mix, and Safety

Mark R. Jacobsen*
University of California, San Diego

November 2010

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. These changes can dramatically alter the optimal level of the standard due to the high value associated with risks to life. I present a novel way to estimate the safety impacts of changes in vehicle class composition, correcting for a selection problem on driver safety that has long existed in the literature. I demonstrate the importance of controlling for driver safety, showing that it can change even the sign of the effect on fatalities. A policy application using my new estimates shows that the present distinction between light trucks and cars in fuel economy rules has very negative consequences for overall safety: Each MPG increment to the standard results in an additional 149 fatalities per year in expectation. I then investigate two alternative regulatory provisions that can produce near-zero changes in accident fatalities.

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* Department of Economics, 9500 Gilman Drive, La Jolla, CA 92093-0508. Email: m3jacobs@ucsd.edu. I thank the University of California Center for Energy and Environmental Economics for providing generous research support, and seminar participants at UC Berkeley, Columbia University, Claremont College, and UC San Diego for helpful comments and suggestions.

1. Introduction

Fuel economy standards have long been a federal policy instrument to reduce gasoline use and are currently slated for an increase in stringency of 35 percent by 2020.[1] One effect of the standards is to alter the composition of the vehicle fleet toward smaller and lighter vehicles, potentially changing vehicle safety. This link with vehicle safety has been the source of strident political debate and is the motivating question here. I estimate how fatal accident risks change as the result of adjustments to fuel economy policy, correcting for the selection problem associated with driving safety behavior.

This question has been the subject of considerable prior research, the early results of which are summarized by the National Research Council (2002): They estimate that 2,000 additional deaths annually are associated with changes in vehicle weight and dimensions to meet existing fuel economy standards.[2] This is based primarily on engineering evidence, relating the safety of occupants in both vehicles to the weight difference between vehicles involved in an accident.

A more recent set of studies emphasize a very different feature in the data: White (2004) and Wenzel and Ross (2005) find that while the larger vehicles discouraged by fuel economy standards are safer for their own occupants, they are so much more dangerous for other vehicles in a collision that removing them from the road represents an improvement.[3] Wenzel and Ross estimate that the external safety costs imposed by large pickup trucks significantly outweigh the private safety benefits to their owners: Thus the switching across vehicle classes that fuel economy standards induce may in fact reduce, rather than increase, accident risks. Gayer (2004) reaches a similar conclusion, that pickups and SUV's present so much risk to others on the road that we might reduce overall risk by switching those drivers into lighter vehicles.

These two sets of results appear to have contradictory safety implications with respect to fuel economy standards: The weight-based engineering studies tend to argue against fuel economy standards since the regulation encourages manufacturers to sell

[1] The Energy Independence and Security Act of 2007 and Environmental Protection Agency (2009).
[2] See Portney et al (2003) and Crandall and Graham (1989) for further discussion.
[3] Some of the estimates in Kahane (2003) also support this finding, though are not the main focus of the report.

smaller vehicles that do more poorly in accidents.[4] On the other hand, the literature emphasizing the danger large vehicles impose suggests just the opposite: That fuel economy standards could improve overall safety by reducing the sales of large vehicles that are dangerous to everyone else on the road.

I propose a novel method that reconciles the two findings by accounting for selection in driving safety behavior: Some types of vehicles are chosen by safer drivers than others and I recover estimates of the direction and degree of this effect. Using my results on driving safety, I can isolate the underlying "engineering" safety of vehicles (holding dangerous behavior of drivers fixed) and relate it to the earlier work on weight differences. At the same time, my estimates of driver safety behavior can explain the more recent findings that large trucks and SUV's appear disproportionately often in fatal collisions.

This selection effect constitutes the central empirical challenge in the paper: I wish to separately identify in the data i) the riskiness of driving behavior (which is determined mainly by unobserved factors), and ii) the physical "engineering" risks in collisions between different kinds of vehicles.[5] I solve this problem by proxying for driving behavior using single-vehicle accidents and crash test results. The equation for single-car accidents, which aids identification of driving behavior, is estimated simultaneously with multi-car accident risks across different combinations of vehicles.

My estimation yields intuitive results: 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. In contrast to the literature, I am able to separate these effects from the physical safety properties of the vehicles themselves.

The second key contribution of the paper involves returning to the motivating question: I combine my empirical results with a simple model of the automobile industry to

[4] An effect known in the industry as "mix-shifting," see Austin and Dinan (2005) and Jacobsen (2010) for a description of the incentives.

[5] 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.

ask how changes in fleet composition affect total fatalities in traffic accidents. Different fuel economy policies produce different types of changes in fleet composition, and I trace these effects through to vehicle accidents.

After controlling for driving behavior, I find that fuel economy regulation that maintains the historical separation of light trucks and cars involves substantial deterioration in vehicle safety. That is, the types of class-switching that are encouraged within passenger cars and within light duty trucks come with adverse safety consequences. This is in support of the engineering literature on vehicle weight that has generally concluded that small vehicles are more dangerous overall. In contrast, I find much better safety outcomes under a unified standard that encourages manufacturers to substitute away from light trucks and into cars.

I show that both of these results hold within a single consistent framework. I also demonstrate the importance of accounting for driver safety and selection: a restricted model where driver safety is held fixed yields very different, and in the case of existing CAFE regulation, opposite results to those I recover from my more flexible model.

The rest of the paper is organized as follows: Section 2 describes the role of safety in U.S. fuel economy policy and Section 3 presents my conceptual model. Section 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 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.[6] 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.

[6] NHTSA (2009).

To further motivate the concern about fuel economy standards with respect to safety consider the (admittedly 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 I 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 I arrive at a cost of $1.55 per gallon saved for increased fatalities alone.[7] 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 argue for careful analysis of the risks, 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

The state of U.S. fuel economy regulation is in flux and I offer an analysis of a variety of possible directions it might take. Each of the 3 regulatory regimes below 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 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

[7] 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.

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.[8] 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.[9]

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} would be incremented.

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[8] 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.

[9] 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 will reflect numerous factors influencing risk and exposure. I categorize these factors into three multiplicative components for the purpose of the model: 1) The "engineering" safety risk that results when two vehicles from the specified classes collide in a standardized setting, 2) the level of risk with which vehicles in each class are driven, 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 engineering risk, driver recklessness , or number of vehicles, the more fatal accidents we should expect.

Define the three components using:

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)

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

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

I normalize the measure of driver riskiness such that it multiplies the 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 engineering risk in a collision of that type, β_{ij}, and the parameters representing bad driving, α_i.

This 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;[10] 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, geography, demographics, 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:

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

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

[10] NHTSA (2008a).

dangerous in an engineering sense or if the drivers who select it just happen to drive particularly badly.

To address this problem I add an equation modeling single-car accidents. I define the count of fatal single-car accidents in vehicle class *i* in location *s* as Y_{is} where:

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

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 across time and space.

x_i The fatality risk to occupants of class *i* in a standardized collision with a fixed object (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 parameterized the risks in collisions according to weight differences. By assigning a complete set of fixed effects for all possible interactions, β_{ij}, I can still recover this information while also adding considerable flexibility in form. The cost to my approach with this parameter 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) estimate risks using a similarly flexible approach for vehicle interactions but importantly do not include driving safety behavior. 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

Three key components of the model above are available as data:

- 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

This section describes my data sources for each.

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 check 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 demonstrated in Section 5, the key safety parameters can be recovered 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.[11] 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 4.1. 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 4.1 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. A further summary of the accident rates in all 100 possible combinations of classes is provided in Table 5.1, discussed below.

[11] 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.

5. Estimation

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.[12]

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 10 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

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

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 hold driving safety behavior fixed across all vehicle classes. The next subsection will add in my correction for driver safety and demonstrate the differences.

For the restricted model I retain the full set of fixed effects on bins *s* and vehicle interactions β_{ij}, making the model:

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

Where the parameters are defined as before, and the ~ modifier indicates the restricted model. Notice that all the α_i parameters have been set to unity and so drop out.

Table 5.1 presents the restricted estimates of $\tilde{\beta}_{ij}$. These 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 cause 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 5.1. 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 simply tend to be driven much more safely.

Results from the full model

With the basic accident rates identified in Table 5.1, I now move on to the full model where driver safety is allowed to vary by class. I find that allowing these effects dramatically alters the core pattern of safety interactions, β_{ij}. The complete set of β_{ij} estimates and standard errors appear in Table 5.2.

A number of key differences appear in the more flexible estimates: Before controlling for heterogeneity in driving behavior large pickup trucks appeared much more dangerous to other drivers than large SUV's (compare columns 7 and 9 of Table 5.1). After correcting for driving safety, the two classes of vehicles now look much more similar (columns 7 and 9 of Table 5.2). 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 also look like the light trucks that they are based on (in fact becoming statistically indistinguishable from them in most accident combinations) after controlling for driving behavior. This validates engineering predictions based on weight and size, resolving the puzzle of why they appear in so few fatal accidents.

My estimates of the α_i parameters mirror the changes in β_{ij} and are plotted along with confidence intervals in Figure 5.1.[13] As indicated minivan drivers are estimated to be the safest among all classes. The dashed line at 1.0 indicates (normalized) average driving safety, meaning 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 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.

6. Policy Simulation

Returning to the motivating policy question, I provide estimates of the influence of fleet composition on total fatalities. The changes in fleet composition I examine correspond to three types of fuel economy rules.

As always, the farther out of sample we wish to look (i.e. very extreme changes to the fleet) the more strain is placed on the structure of the model. 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 s.[14] The changes as the result of fuel economy rules span only a small piece of this variation.

[13] This is partly by construction: To fit the data, improvements in driving safety will generally be reflected by declines in engineering safety.
[14] It ranges from 10% (high-income, urban, daytime) to 22% (low-income, rural, night).

Method

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 6.1 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 6.2 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. 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).

[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.

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. Being able to track drivers as they move from one vehicle to another allows me to properly incorporate my estimates of α_i.

It may help to illustrate with an example: If the policy causes a lot of large-pickup drivers to 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.[16]

To compute the new driving safety parameters, $\hat{\alpha}_i$, I take a quantity weighted average of the safety characteristics of drivers from all the other classes who have switched into class *i*, 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 restrict my study to the 10 classes above, which include all passenger vehicles regulated by CAFE. 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

[16] I acknowledge that some dangerous driving behaviors may disappear when drivers switch vehicles, but argue that the most important ones like driving at night, in rural areas, under the influence, or without paying proper attention will tend to remain even after drivers switch vehicles.

passenger vehicles that collide with commercial vehicles using the same risk factors I estimate for single-car accidents.[17]

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 (perhaps increasing that).[18] 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.[19] 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 correcting for driver behavior would be unaffected.

Results of policy

The results of the three policy simulations are contained in Tables 6.3 through 6.5. 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.

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[17] This is a reasonable approximation since the size of commercial trucks means collisions with passenger vehicles resemble collisions with fixed objects.
[18] 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.
[19] 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.

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

The left panel of Table 6.3 displays the change in total traffic deaths that are predicted using the restricted model. Driving behavior is not taken into account. The 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, allowing for selection on driving behavior at the class level. My 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 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 alcohol or 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 additional fatalities I predict.

2) Unified standard achieving a 1.0 MPG improvement

Table 6.4 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 is just a repeat of 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 just so happens 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 6.5 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

Identifying driver behavior without using crash test data

It is possible to identify the main model (including fixed effects for 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.[20] 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.

The first two columns of Table 7.1 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?

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

I investigate the robustness of my simulation results by introducing an entirely separate set of substitution elasticities, shown in Table 7.2. 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 7.1 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

Finally, I investigate the robustness of my findings in a number of subsamples of the data. Columns 3 through 5 of Table 7.3 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.[21] 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

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

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 model of vehicle accidents that accounts for selection and driving safety behavior across classes. This problem has presented a challenge in numerous prior studies, and I show that correcting for it significantly alters conclusions about fleet composition and safety.

The underlying empirical model offers two key results: First, there is considerable diversity in driving behavior across vehicle classes: The most dangerous drivers (pickup truck owners) are three 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 impart the most damage to others.

To address the motivating policy question about safety and fuel economy regulation, I experiment with three policy simulations. The results provide a new understanding of how fleet composition changes associated with fuel economy influence overall safety:

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) only further increasing the cost of this type of regulation.[22]

In contrast, I find that a unified fuel economy standard has almost no harmful effect on safety. The additional fatalities incurred by switching to smaller and lighter cars and trucks are offset almost exactly by switches between the two categories: Moving people out of light trucks and into passenger cars confers an overall safety benefit.

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 uncover additional ways to adjust fuel economy rules to protect or even improve safety. The policy simulations might similarly be explored in more depth, with attention given to inter-firm dynamics or the credit-trading provisions in upcoming federal regulation.

[22] 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.

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Table 4.1: Summary Statistics

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 2005-2008.
[2] In billions of miles per year (2008 National Household Transportation Survey).
[3] Results from NHTSA testing 1992-2008.

Table 5.1: 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 Poisson estimation of the multi-car accident equation alone, with all class-level safety effects restricted to unity.

Table 5.2: Estimates of β_{ij} in Full Model[1]

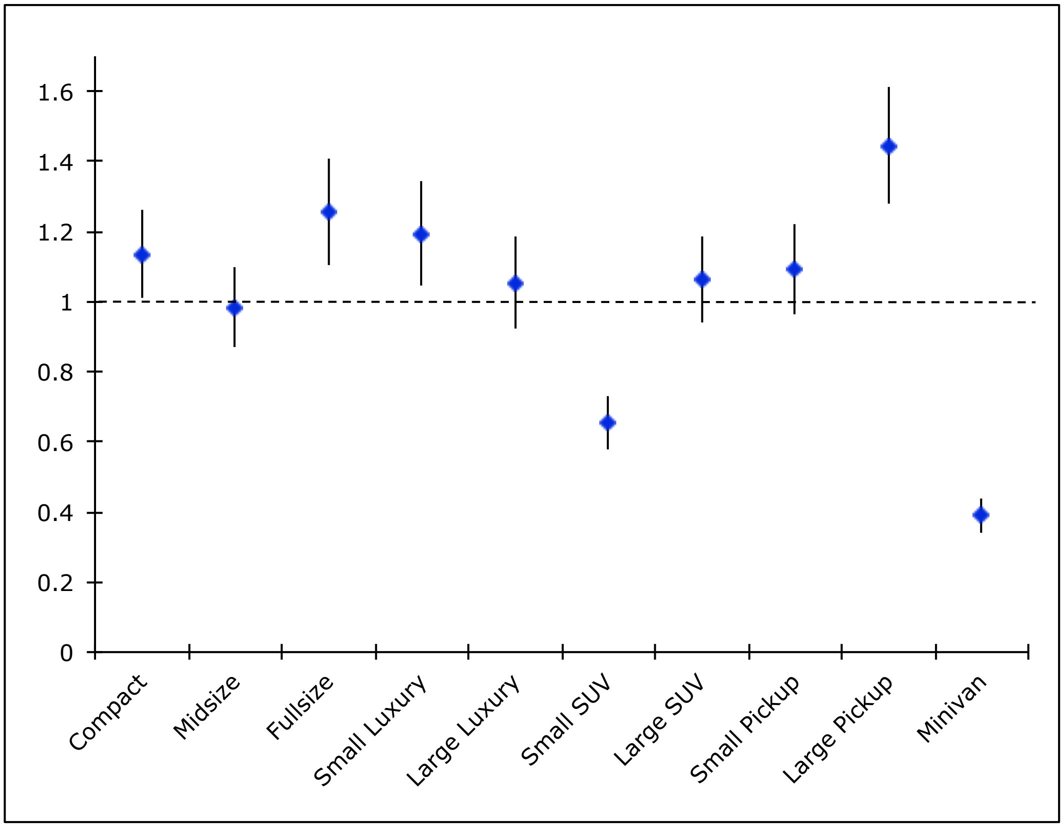
	Compact	Midsize	Fullsize	Small Luxury	Large Luxury	Small SUV	Large SUV	Small Pickup	Large Pickup	Minivan
Compact	5.8 (0.7)	8.1 (1.0)	7.7 (1.0)	5.1 (0.7)	8.3 (1.1)	13.3 (1.6)	13.3 (1.6)	10.9 (1.4)	16.3 (1.9)	16.7 (2.1)
Midsize	4.8 (0.6)	7.4 (0.9)	6.5 (0.9)	4.4 (0.7)	7.2 (1.0)	10.6 (1.3)	11.8 (1.4)	10.1 (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)

Poisson regression
Number of obs: 308880
Log likelihood: -89320.9
Wald chi2(297): 233211.7

297 total parameters estimated. 100 displayed, remaining 197 fixed effects summarized in Figure 5.1 and also available on request.

[1] Standard errors are shown in parentheses, estimates are from simultaneous Poisson estimation of the multi-car and single-car accident equations, with the inclusion of class-level safety effects.

Figure 5.1: Estimates of α_i in Full Model[1]



[1] The bars indicate 95% confidence intervals. Estimates are from simultaneous Poisson estimation of the multi-car and single-car accident equations. The average driving safety behavior is normalized to 1.

Table 6.1: 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 6.2: 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 6.3: 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 6.4: 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 6.5: 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 7.1: 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 7.2: 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 7.3: 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