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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, potentially influencing accident safety. I introduce a model of the fleet that captures risks across interactions between vehicle types while simultaneously recovering estimates of unobserved driving safety behavior. The model importantly includes the ability to consider the selection of driver types across vehicles. I apply the model to the present structure of U.S. fuel economy standards and find an adverse effect on safety: Each MPG increment to the standard results in an additional 149 fatalities per year in expectation. I next show how two alternative regulatory provisions, including one slated to enter effect next year, can fully offset the negative safety consequences; minor changes in the regulation produce a robust, near-zero change in accident fatalities while conserving the same quantity of gasoline.

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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 overall accident safety. The direction and magnitude of the effect depends on the set of interactions between all vehicles in the fleet: larger vehicles tend to offer their own occupants greater safety, but do so at considerable expected cost to the drivers of smaller cars. I show how the effects of vehicle safety can dramatically change the cost-benefit calculus for new fuel economy rules phasing in through 2016.[1] The need to understand the size and direction of the relation between fuel economy and safety is further underscored by the announcement of even stronger policy through 2025, nearly doubling the current fuel economy requirement.[2]

There is a long related literature on vehicle engineering and safety, much of it focusing on specific physical characteristics of vehicles like weight or the inclusion of new safety technologies. Kahane (2003) and the National Research Council (2002) provide summaries. Evans (2001) and Anderson and Auffhammer (2011) parameterize the effect of weight in particular and make a careful effort to control for driver selection. In general this literature finds that heavier vehicles offer additional protection in accidents, but in cases where two vehicles are involved the extra weight imposes risk on the other driver. The National Research Council (2002) applies one such simple relationship between overall vehicle safety and weight and suggests that 2,000 additional deaths annually could be associated with existing fuel economy standards.[3]

There is also a recent literature that investigates the danger that light trucks specifically (a category including pickups, minivans, and SUV's) pose when they are involved in an accident with a sedan. White (2004) shows that the protective effect of light trucks for their own drivers combines with severe external risks to create an arm's race in

[1] Environmental Protection Agency and Department of Transportation (2010). There were 37,261 U.S. traffic fatalities in 2008.
[2] The White House Office of the Press Secretary (2011).
[3] See Portney et al (2003) and Crandall and Graham (1989) for further discussion.

vehicle choice. Gayer (2004) examines the safety of light trucks using snowfall as an instrument to predict their frequency in the fleet. He shows that there is a significantly higher overall fatality risk in areas with a greater number of light trucks, suggesting that fuel economy incentives – if they acted to discourage pickups and SUV's – might in fact have the opposite effect, improving safety outcomes.

The first main contribution of this paper is an econometric model that flexibly nests both strands of the literature. My model provides what I believe is the first approach to consider safety in counterfactual fleets where characteristics like weight can change simultaneously with composition across vehicle classes. A key challenge is to model driver selection into vehicle types, observing that drivers will re-optimize over their choice of vehicle as fuel economy policy changes the composition of the fleet. My estimation technique introduces a semi-parametric method to measure this effect of unobserved driver behavior: in policy counterfactuals I show that the ability to capture driver behavior is pivotal to the policy results, changing the sign of the estimated welfare impacts.

My estimation approach begins with a system of equations describing single-vehicle and two-vehicle accident fatality rates, all expressed per mile driven. In order to abstract from weight or the light truck definition in isolation I bin vehicles into classes (ten in the dataset I employ) spanning the wide variety of sizes, weights, and shapes in the fleet. The model allows estimates of the internal and external safety costs when vehicles in each bin interact with every other.[4] Restrictions across the equations allow me to empirically separate unobserved driver risk behavior from underlying vehicle safety.

The second contribution here, before moving to the policy question on fuel economy standards, lies in the empirical estimates themselves. I use U.S. accident data to estimate a matrix of risks across 110 specific accident types, all estimated without parameterizing vehicle characteristics.[5] When cutting this matrix along the dimension of weight I am able

[4] The estimates are semi-parametric in this sense since no restrictions are placed on the combination of physical characteristics in a bin. Among other dimensions classes differ by weight, wheelbase, engine size, fuel economy, and passenger capacity.
[5] There are 100 types of two-car accidents, corresponding to all interactions of vehicles across bins, and 10 types of single car accidents.

to show that my empirical results are consistent with the earlier literature examining weight in isolation. If I instead divide my estimates according to class, light truck or sedan, I further find the results are consistent with the literature looking at the dangers imposed by light trucks. Finally, and in contrast to either of these earlier approaches, the matrix of estimates also captures safety interactions along all other physical dimensions where vehicle bins differ.

My empirical results also contain a novel measure of the residual riskiness of drivers who select into different types of vehicles, expressed up to a constant. Since I can allow all components of driver risk to remain unobserved these estimates capture, for example, a tendency to drive drunk,[6] the safety of roads in the driver's geographical area, and Peltzman-type effects where the protective nature of a vehicle itself may affect driving behavior.

Finally, a third key contribution of this work returns to the motivating question, applying my empirical model of the vehicle fleet to consider the safety impacts of fuel economy policy. I consider three policy variants, all based on current or proposed fuel economy rules. The estimated safety impacts of the first policy, based on the historical Corporate Average Fuel Economy (CAFE) rules, depend pivotally on my ability to model driver behavior: 149 additional annual fatalities are predicted per mile-per-gallon increment. I next consider a "unified" standard that encourages smaller vehicles overall, now reducing both weight and the number of light trucks. Unlike earlier studies, I can estimate the degree to which these factors offset. The increase in fatalities under the unified rule is only 8 per year, with a zero change included in the confidence band. Finally, I consider a “footprint” type rule similar to the provisions in fuel economy standards set through 2016. It too has a near zero impact on safety. I explore robustness of these results to a variety of factors including Peltzman-type selection effects, weather, age of vehicles, driver versus passenger fatalities, and the potential frailty of older drivers in accidents.

I limit the policy analysis to the example of fuel economy rules, but since the model presented here allows consideration of arbitrary counterfactual fleets it could also be applied

[6] Levitt and Porter (2001) provide an innovative method to estimate drunk driving rates using innocent vehicles in accidents as control, but in most cases (including the present study) such personal characteristics are difficult to observe.

to a number of other questions. For example, the U.S. "cash-for-clunkers" program as described in Knittel (2009) or the incentives to switch among new and used vehicles in Busse, Knittel, and Zettelmeyer (2011) may produce changes in safety that importantly alter the economic efficiency of policy. The definition of vehicle bins is flexible such that expansions or redefinitions of the vehicle set would allow future investigation of the variety of policies aiming at influencing composition of the vehicle fleet.

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 the model. 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. Section 7 considers three alternative specifications and addresses robustness.

2. Safety and Fuel Economy Regulation

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.[7] 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.

To 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 are attributed to changes in the composition of the vehicle fleet due to the 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.[8] This does not consider

[7] NHTSA (2009).
[8] 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.

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.[9]

Conversely, a finding that accident risks improve with stricter fuel economy regulation 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, with the rule through 2016 now complete (Environmental Protection Agency and Department of Transportation [2010]), while regulatory provisions beyond 2016 remain to be 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 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 was introduced in California as part of Assembly Bill 1493, and is under consideration federally.[10] It regulates all vehicles together

[9] See Parry and Small (2005).
[10] 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.

based only on fuel economy. This includes the effects above while simultaneously 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 also 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.[11]

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.

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

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

[11] 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.

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:

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

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 term 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 relative to an average driver. 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:

$$\text{Probability of a fatal accident in vehicle } i \mid i,j \text{ present} = \alpha_i \alpha_j \beta_{ij} \qquad (3.3)$$

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;[12] 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:

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

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.

[12] NHTSA (2008a).

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. Note that the assumption is not that the absolute risk of single and two-car accidents are always proportional (clearly single car accidents are more frequent at night, for example) but rather it restricts the way that driver behavior multiplies those risks.

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

I assemble data on each of the three variables needed to identify the parameters of (3.4) and (3.5):

- Comprehensive count of fatal accidents, Z_{ijs} and Y_{is}
- The number of vehicle miles driven in each class, n_i
- Crash test data to describe risks in single-car accidents, 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 in actual accidents very close to proportionally (Herman (2007)). This is important for my application since equation (3.5) requires a measure that reflects proportional 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.[13] 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, all else equal.

The crash test data is more difficult to defend than my other sources since it relies on the ability of laboratory tests to reproduce typical crashes and measure injury risks. I therefore offer an alternative specification in Section 7 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 summary of fatal accident counts, reflecting fatalities both in the vehicle and those of other

[13] 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.

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.

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.[14]

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:

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

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, or category definition as a light truck) 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.

Quantity 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%.[15] Kahane (2003) focuses on own safety risk: for passenger cars the central estimate of the protective effect is 44% per 1000 pounds of weight.[16] 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

[15] 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%.
[16] 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.

type. I now have evidence to support this: the selection effects I find among different types of light trucks are much stronger than those among passenger cars.

Anderson and Auffhammer (2011) also 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 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, fuel economy, and fleet composition turns on three factors: The underlying engineering causes of fatal accidents, the driving risk of the individuals who choose different vehicle types, and the re-optimization of vehicle choices that occurs due to the regulation. I recover the first two of these as empirical estimates in my framework above. The third, modeling which individuals change their car choice as a result of the standard, is described here.

The first stage of the simulation involves applying the shadow costs of policy to vehicle choices: Implicitly, existing policy increases the purchases of small cars and decreases the purchases of large cars in order to meet an average target. Policy also creates an incentive for technological change that I am assuming does not alter safety in itself; I instead focus on the changes in fleet composition. All of my empirical measures are per-mile driven, and that continues to hold in simulation. The vehicle choice model assumes constant own and cross- price elasticities of demand taken from the literature, and that consumers re-optimize based on the shadow costs present under different types of fuel economy standard.

The behavior of drivers, a key focus of this paper, also enters the simulation. I first assume that drivers carry their residual term with them as they switch vehicles. For example if a minivan or SUV driver switches to a large sedan, that will lower (all else equal) the fatality rate per mile in sedans. On the other hand, if a pickup truck driver switches to the same sedan that would increase the fatality rate per mile in sedans. Simulating a movement of the residual with the driver assumes that exogenous characteristics of drivers make up most of the safety residual (age, gender, safety of roads in local area, income, alcohol use, children in the vehicle, etc.).

However, Peltzman (1975) points out that larger, safer vehicles should induce more risk-taking behavior. Gayer (2004) also makes the case that light trucks and SUV's are more difficult to drive, working in the same direction as the Peltzman effect.[17] In my context the Peltzman effect means that a portion of the safety residual should stay with the vehicle class even as drivers re-optimize. I compute an upper bound on these effects and allow them to enter a second set of simulations. Intuitively, I find that Peltzman-type effects make all fuel economy standards look better on safety since we are now arguing that smaller vehicles themselves cause better driving behavior. Importantly my main policy conclusions, including the adverse effect of the current standard and the improvement offered by a unified standard, remain fully robust.

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 s.[18] The changes as the result of fuel economy rules span only a small piece of this variation.

[17] The recent widespread adoption of unibody SUV designs and electronic traction and stability control may reduce this effect.
[18] It ranges from 10% (high-income, urban, daytime) to 22% (low-income, rural, night).

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). I also investigate the robustness of my results to alternative elasticities. To determine the change in vehicle choices I combine the matrix of elasticities with the shadow tax implicit in fuel economy regulation.[19] 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. 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

[19] 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.

their footprint (SUV's). This implies relatively little switching across vehicle types and therefore only small changes in safety.

Since the cross-price elasticities describe the full pattern of substitution I can calculate both the new composition of the fleet and also track the types of drivers as they switch across vehicles. Depending on which types of drivers are switching into the smaller vehicles their accident rates per mile can either rise or fall. 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.

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 residual 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.[20]

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 in a "rebound" effect).[21] I focus here on fatalities per mile driven in order to keep the simulation transparent: to the extent that either the increase in overall miles or decrease in fleet size is important it will scale total fatalities up or down. The comparison in policy provisions that I focus on is unaffected by changes in overall scale.[22]

iii) *Pedestrians and bicyclists*: About 14% of fatalities involving passenger vehicles are pedestrians and bicyclists. These fatality rates 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.[23] 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.

Results of policy simulations

The results of the three main policy simulations are contained in Tables 7 through 9. I compute standard errors for the total change in fatalities in each case by using the delta

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[20] 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).

[21] 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.

[22] Differential changes in driving across vehicle types will have more complicated effects and an extension to the paper could involve a richer simulation model to account for this. These effects would not change the estimation strategy or empirical results.

[23] 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 somewhat higher for larger vehicles. Surprisingly, the opposite effect holds within cars: larger vehicles have lower pedestrian fatality rates.

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, including 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 driver effects here 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. 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

Driver-vehicle specific safety effects correlated with size

Peltzman (1975) argued that safer vehicles (in particular those with seatbelts installed) will be driven more aggressively as a result of the driver's tradeoff in utility.[24] Gayer (2004) presents evidence of a similar effect, where drivers in light trucks appear to take more risks or have less control when driving. Correlation of this type between vehicle size and unobserved driving behavior can be expected to improve the safety outcomes associated with all fuel economy standards, since it assumes that putting people in smaller vehicles causes safer driving.

I am able to investigate this in the context of my model by further decomposing the safety residual into two pieces. I define the first piece as being all of the residual driving safety that is correlated with the own-safety of the vehicle. In that sense it is an upper limit on the size of the Peltzman effect.[25] The second portion is whatever idiosyncratic variation remains in my estimated driving safety residuals. In the alternative simulations below I assume that the first portion stays together with the vehicle type (i.e. is adopted by drivers once they switch to that vehicle). The idiosyncratic part continues to move with the driver. Table 10 presents the results of these policy experiments. The third column is my upper bound on the Peltzman effect over all driving safety residuals. The fourth column controls first for census region (there are more light trucks and dangerous roads in the west) and then applies the same method to divide the residual into two pieces.

[24] Subsequent empirical research has shown this effect may be small, see Cohen and Einav (2003).
[25] Unobserved countervailing selection in initial vehicle choice could potentially make the Peltzman effect even larger; these more extreme cases could still be modeled in simulation, possibly using estimates from other studies.

As expected, the outcomes in Table 10 show that all fuel economy standards are improved if drivers become safer when moved to a smaller vehicle. However, even at the limit defined above I show that the existing fuel economy standard continues to have adverse effects on safety. Controlling for census region seems reasonable (as driver residence is unlikely to change with fuel economy standards), and the result becomes closer to my central case.

More important, the improvement that can be offered by unifying the standard appears robust to both of the cases where I allow vehicle size to itself influence driving behavior. This is shown in the final row of the table. Indeed, because the difference in policies is maintained and overall safety is improved we see that the unified standard begins to offer substantial improvements in overall safety in the final column of the table. Across the range of possibilities we see the existing standard causes robust declines in safety, while a unified standard is at worst neutral with regard to safety, and at best can offer substantial gains.

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.[26] 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:

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

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

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

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

The first two columns of Table 11 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 12. These are reported in Kleit (2004) and are also employed by Austin and Dinan in their 2007 study. 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 11 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 13 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.[27] 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.

[27] Loughran and Seabury (2007) investigate this issue in detail.

8. Conclusions

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 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 both within and across vehicle categories. The framework has application to fuel economy policy (the simulations performed here) and also to a much broader set of policy initiatives. I show that in the case of fuel economy, correctly accounting for driver behavior 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 inside 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 use these results to address 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.[28] Intuitively, my estimates measure the degree to which greater diversity in the vehicle fleet leads to more fatal accidents. Current CAFE standards,

[28] 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.

by encouraging light trucks while at the same time making passenger cars smaller and lighter, increase the diversity of the fleet.

In contrast, I find that a unified fuel economy standard has almost no harmful effect on safety. Two effects are operating in opposing directions: weight reductions increase risk while substitution away from light trucks makes the fleet more homogeneous. My model implicitly compares the relative importance of these two effects, finding that they offset almost exactly under the shadow costs implied by a uniform fuel economy standard.

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

	Count of Accident Fatalities[1]		Total Miles	Crash Test
Class	Own Vehicle	Other Vehicle	Driven[2]	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] One and 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. The head-injury criterion (HIC) score has been shown to be closely and linearly related to fatality rates (when controlling for driver behavior, a doubling in the score should correspond to a doubling of fatality rates).

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] Based on zip-code level classifications from the U.S. Census.
[2] Relative frequencies are calculated as accident counts within group divided by total miles traveled. A combination of vehicle popularity and driver behavior within group determines the accident with greatest relative frequency.

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. These coefficients provide a summary of fatal accident rates without controlling for driver behavior.

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. These are identified up to a constant and are normalized here such 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 Own and Cross-Price Demand Elasticities by Class[1]

	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

[1] These elasticities are derived from Bento et al (2009) and are used in the central case of the policy simulations. I investigate the robustness of the results to alternative elasticities (see Table 12).

Table 6: Average Fuel Economies and Shadow Taxes by Class

Class	Fuel Economy (MPG)	***Shadow Tax of Policy Increment***[1] 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

[1] The shadow taxes and shadow subsidies are placed by the fuel economy policy and differ according to the type of standard in place. They are proportional to the distance of each vehicle (in gallons-per-mile) from the applicable fuel economy target.

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[1]

	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)

[1] The unified standard induces two kinds of changes in the fleet, both of which are captured together in these results. i) Small cars replace large ones and small trucks and SUV's replace large trucks and SUV's. ii) Light trucks overall (the second set of five classes) replace cars overall (the first set of five classes).

Table 9: Effect of a Footprint Fuel Economy Standard on Total Traffic Deaths[1]

	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)

[1] A footprint standard (by design) involves much smaller changes in the composition of the fleet than either of the first two policies simulated. The changes in accident fatalities are similarly small.

Table 10: Peltzman Effects and the Influence of a Driver-Vehicle Specific Residual[1]

	No driver effects	Full model (central)	Peltzman effect (upper limit)	Peltzman within census divisions (upper limit)
Current CAFE within fleet	-135.02 (6.15)	149.47 (9.36)	69.80 (9.36)	101.72 (9.36)
Unified standard	-12.14 (3.81)	8.50 (4.35)	-57.00 (4.35)	-64.43 (4.35)
Footprint-based standard	26.88 (1.28)	6.27 (1.52)	-18.94 (1.52)	-4.49 (1.52)
Improvement offered by unified standard	**-122.9**	**141.0**	**126.8**	**166.1**

[1] The values in the right two columns allow driving behavior to improve as drivers switch to smaller vehicle classes. They are upper limits in the sense that all of the correlation between estimated driver behavior and size is attributed to the vehicle (e.g. large vehicles are driven more aggressively or are more difficult to control). As expected, all safety outcomes from CAFE improve in these columns. The sign of the effect on the current CAFE standard is preserved and the improvement offered by a unified standard is robust.

Table 11: Alternative Identification Strategy and Simulation Elasticities[1]

	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)
Unified standard	-12.14 (3.81)	8.50 (4.35)	7.31 (21.11)	32.97 (2.85)
Footprint-based standard	26.88 (1.28)	6.27 (1.52)	-47.55 (5.72)	8.18 (1.27)

[1] My alternative identification strategy avoids the use of crash test data entirely. The standard errors are much higher given the additional cross-equation restriction needed, but the overall effects are preserved. Results are similarly robust to the alternative substitution elasticities used in the choice model.

Table 12: 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

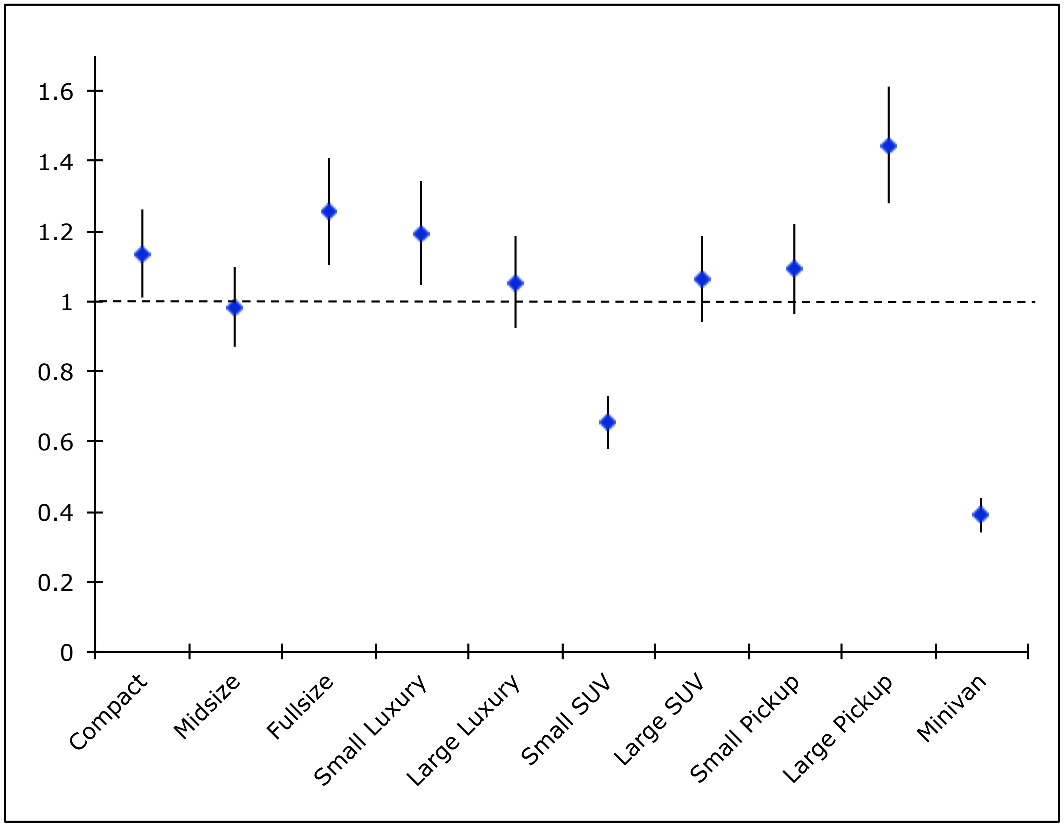
[1]Elasticities from Kleit (2004) aggregated to match the ten class definitions in my model. In order to isolate the effects of fleet composition I also proportionally adjust the cross-price elasticities such that fleet size is exactly maintained.

Table 13: 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
Unified standard	-12.14	8.50	6.27	-2.47	8.26
Footprint-based standard	26.88	6.27	0.56	3.36	6.99
Fraction of accidents		1.00	0.52	0.77	0.90

[1] Changes in overall safety through time (perhaps most importantly the airbag requirement in 1998) do not affect the relative safety performance of classes enough to alter my conclusions on fuel economy rules. The potential frailty of older drivers and selection of vehicle type by weather conditions similarly have very small impacts on the results.

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.