

Fuel Economy, Car Class Mix, and Safety

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Fuel economy standards, which are rapidly increasing in stringency in the United States, typically alter the composition of the vehicle fleet toward smaller and lighter vehicles.¹ The link between these compositional changes and safety has the potential to dramatically alter the costs of saving gasoline via fuel economy regulation and is the issue I address here. I provide a new empirical model of accident fatality risks and combine it with a simulation model of vehicle fleets and fuel economy standards.

This issue is particularly important given the risks that driving imposes to life: More than 37,000 fatalities were recorded in US automobile accidents in 2008.² Proportional increases or decreases in this rate, even relatively small in magnitude, have substantial implications for the cost of gasoline savings.

The prior literature can be divided into two general strands, the first of which is summarized in a report from the National Research Council (NRC, 2002). Based on engineering studies of vehicle weight and safety, they estimate that 2,000 additional deaths annually are attributable to vehicle size changes from existing fuel economy standards.³ Using conservative assumptions (detailed in an Appendix available on the *AER* website), this corresponds to a cost of \$1.55 per gallon of gasoline saved.

A second, more recent set of studies emphasize a very different feature in the data: Ted Gayer (2004), Michelle J. White (2004), and Thomas P. Wenzel and Marc Ross (2005) show that while the larger vehicles discouraged by fuel economy standards are safer for their own

occupants, they impose a severe cost on other vehicles in a collision. Removing large vehicles from the road via fuel economy standards could therefore create an improvement in overall safety.

My main empirical contribution is to reconcile these findings by accounting for selection in driving safety behavior: Controlling for driver behavior by vehicle type allows me to isolate the underlying “engineering safety” of vehicles and relate it to the earlier work on weight differences. At the same time, my estimates of driver behavior can explain the more recent findings that large trucks and SUVs are represented disproportionately often in fatal collisions.

Separating the riskiness of driving behavior (which comes from both observed and unobserved factors, such as the propensity to drive on dangerous roads) is the central empirical challenge.⁴ I solve it by proxying for driving behavior using single-vehicle accidents and crash test results, recovering an intuitive set of estimates: Minivans and small SUVs have the lowest risks attributable to the driver’s behavior and location, while pickup trucks and large sedans are associated with the highest risk.

Returning to the motivating policy question, I combine my new empirical results with a simple model of the automobile industry to ask how changes in fleet composition alter fatality risks. After controlling for driver selection, I find that fuel economy regulation that maintains the historical separation of light trucks and cars involves substantial deterioration in vehicle safety. In contrast, I find much better safety outcomes under a unified standard that encourages manufacturers to substitute away from light trucks and into cars.

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¹ An effect known in the industry as “mix-shifting,” see David Austin and Terry Dinan (2005) and Mark Jacobsen (2010) for a description of the incentives.

² National Highway Traffic Safety Administration (NHTSA 2009).

³ See Paul Portney et al. (2003) and Robert W. Crandall and John D. Graham (1989) for further discussion.

⁴ 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. Steven D. Levitt and Jack 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.

TABLE 1—VEHICLE CLASSES, ACCIDENT RATES,
AND ESTIMATED DRIVER EFFECTS

Vehicle class	Single-car fatality rate ^a	Crash test fatality risk	Average α_i^b
Compact	14.3	1.00	1.14 (0.06)
Midsize	11.3	0.93	0.98 (0.06)
Fullsize	10.2	0.67	1.25 (0.08)
Small luxury	13.5	0.80	1.19 (0.08)
Large luxury	11.9	0.89	1.05 (0.07)
Small SUV	9.4	1.18	0.65 (0.04)
Large SUV	12.8	1.00	1.06 (0.06)
Small pickup	15.9	1.26	1.09 (0.07)
Large pickup	18.2	1.11	1.45 (0.08)
Minivan	4.9	1.09	0.39 (0.02)

^aPer billion miles traveled

^bStandard errors in parentheses

I. Empirical Model

I model the count of fatal accidents between each combination of vehicle classes as a Poisson random variable. Vehicle classes in the data represent ten sizes and types of cars, trucks, SUVs and minivans; covering all passenger vehicles in the United States. They are listed in Table 1.

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 . Counts of accidents reflect all factors influencing risk and exposure. I categorize these into three multiplicative components: i) β_{ij} reflects the engineering safety risk of a fatality in vehicle i when vehicles from classes i and j collide, abstracting from all aspects of driver behavior or location. ii) α_i represents the portion of risk attributable to the behavior or location of drivers in class i . iii) n_{is} is the number of vehicles of class i that are present in bin s .

The greater any of these components—engineering risk, drivers' risk, and number of vehicles—the more fatal accidents are expected. I

normalize the measure of driver riskiness such that it multiplies the fatality risk. Values of α_i come from individual-level factors that may be unobservable. The subscript s indicates bins of the data by 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.

Combining the three terms, I model the count of accident fatalities as:

$$(1) \quad E(Z_{ijs}) = n_{is}n_{js}\alpha_i\alpha_j\beta_{ij}.$$

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;⁵ such accidents give drivers little time to alter behavior based on attributes of the other vehicle or driver.

Given that the α_i terms include unobservable driving behaviors it is impossible to estimate equation (1) alone; it can't be separately determined if a vehicle class is dangerous in an engineering sense (captured in β) or if the drivers who select it just happen to drive particularly badly (captured in α).

To separate the two parameters, I include single-car accidents in the model defining Y_{is} as the count of single-car fatalities:

$$(2) \quad E(Y_{is}) = n_{is}\alpha_i\lambda_sx_i,$$

where n_{is} and α_i are as above and λ_s flexibly captures factors specific to bin s that influence the frequency of single-car accidents relative to multicar accidents. x_i refers to the fatality risk to occupants of class i in a standardized collision with a fixed object. This will be reflected (up to a constant) using crash test results. The key restriction across equations (1) and (2) 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.

Much of the previous work focusing on the influence of weight of vehicles (see Charles J. Kahane 2003) has parameterized the risks in

⁵ NHTSA (2008b).

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 adding considerable flexibility in form. Wenzel and Ross (2005) estimate risks using a similar 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 each of the α_i parameters to unity. The parameter estimates turn out to be quite different, so much so that the primary policy implication is reversed in sign.

II. Data

Accident counts come from the Fatal Accident Reporting System (FARS), which comprehensively records each fatal automobile accident in the United States. This dataset is complete, of high quality, and includes 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 a hospital. I make use of these in a series of robustness checks available in the Appendix. For my main specification I pool data for the three years 2006–2008. My measure of n_{is} comes from the 2008 National Household Transportation Survey, detailing the driving patterns and vehicles owned by more than 20,000 US households.

The second key data component is crash test results (x_i in the model above), which I take from the National Highway Traffic Safety Administration (NHTSA). 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 (Irving P. Herman 2007), important for integration with my model. Fatality rates in single-car accidents and the average HIC by vehicle class are shown in the first and second columns of Table 1.

III. Estimation

Since the parameters for driving behavior and quantity are relevant only up to a constant (they express relative riskiness and vehicle density, respectively) I combine them into a single term for estimation: $\delta_{is} \equiv n_{is} \alpha_i$. The average risks by class α_i can be recovered after estimation using

aggregate data on miles traveled.⁶ I estimate the parameters of the following two equations:

$$(3) \quad Y_{is} \sim \text{Poisson}(\omega_{is})$$

$$E(Y_{is}) = \omega_{is} = \delta_{is} \lambda_s x_i$$

$$(4) \quad Z_{ijs} \sim \text{Poisson}(\mu_{ijs})$$

$$E(Z_{ijs}) = \mu_{ijs} = \delta_{is} \delta_{js} \beta_{ij},$$

where x_i and the realizations of Y_{is} and Z_{ijs} are data. All remaining parameters are estimated simultaneously using maximum likelihood. Estimates are robust to fitting a negative binomial distribution in place of the Poisson. For comparison with other work, and to demonstrate the importance of allowing driver selection across vehicle classes, I compare my estimates with a restricted version of the model. It is estimated identically to the above with the restriction that α_i is equal to unity for all classes.

IV. Empirical Results and Policy Simulation

I first estimate the restricted version of the model, such that all drivers are assumed to have average risk. This version of the model reflects aggregate trends in the data well but conflicts with typical assumptions in the engineering literature. For example, minivans, while much larger and heavier than the average car, appear to impose very few fatalities on any other vehicle type.

My full model resolves this puzzle by describing a set of selection effects in vehicle safety across classes. The third column of Table 1 displays estimates of α_i normalized to 1.0 for a driver of average risk. Minivans and small SUVs receive the lowest coefficients, with minivan drivers having fatal accident rates less than half that of the average driver. The drivers of large cars and pickup trucks bring the highest risks.

The corresponding set of estimated β coefficients appears in the Appendix, both before and after accounting for driver behavior. The correction for driver selection reconciles accident risks across classes with engineering predictions: Minivans appear similar to the light trucks they are based on in terms of engineering risk,

⁶ See Appendix for the derivation.

and light vehicles more generally appear riskier than heavy ones. My corrected coefficients also reflect the weight externality: The β parameters reflecting standardized risk in accidents between compacts and large pickup trucks, for example, show a risk nearly eight times larger for occupants of the compact car.

I apply my estimates to a simple model of fuel economy standards in the US, considering two possible regulatory regimes. The first is an extension of 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. This produces a distinctive pattern of shifts to smaller vehicles within each fleet, but without substitution between cars and trucks overall. I hold the total number of vehicles and riskiness of drivers fixed, keeping track of individual drivers as substitution across vehicle classes occurs.

The first column of Table 2 displays results from my restricted model, before accounting for selection. A reduction of 135 fatalities per year is predicted from a 0.1 mile-per-gallon (MPG) increase in fuel economy via compositional changes.⁷ The second column reflects the full model and presents a very different conclusion: An increase of 150 fatalities is predicted. Intuitively, I am finding that much of the danger of large vehicles comes from their drivers, who will remain on the road and are now more vulnerable in accidents. The effect is particularly strong for single-car accidents, which represent nearly two-thirds of fatalities in the data.

My second policy simulation is a unified standard that regulates all vehicles together based only on fuel economy. This has the effect of shifting consumers away from trucks and SUVs and into cars. The results appear in the fourth column of Table 2, showing an increase of only eight fatalities per year with a zero change included in the confidence bounds. This significant improvement over an increment to current CAFE comes as the result of shifts out of trucks and into cars, which I predict confers a safety benefit even after accounting for driver behavior. The benefit almost exactly offsets the deterioration of safety within the car and truck fleets due

TABLE 2—CHANGES IN ACCIDENT RISK UNDER ALTERNATIVE POLICIES

	Increment to CAFE		Unified standard	
	Restricted model ^a	Full model	Restricted model	Full model
Compact	368.6	413.6	273.5	251.0
Midsized	-135.5	-101.9	47.0	58.6
Fullsize	-112.0	-106.1	5.2	4.0
Small luxury	-46.8	-44.2	6.5	5.6
Large luxury	-60.2	-57.0	-8.1	-6.9
Small SUV	94.8	187.7	-24.3	-7.0
Large SUV	-113.0	-109.0	-81.7	-81.2
Small pickup	59.7	69.3	-53.0	-52.0
Large pickup	-223.2	-222.3	-161.6	-161.8
Minivan	32.6	119.3	-15.6	-1.8
Total	-135.0	149.5	-12.1	8.5
Standard error	(6.1)	(9.4)	(3.8)	(4.3)

^a Values are the predicted change in number of annual traffic fatalities occurring in each vehicle class.

to the downsizing of vehicles, for a near-zero change in total fatalities.

V. Future Work

My empirical estimates can inform a variety of other policy considerations, importantly including the “footprint” based standard that is in effect for the 2012–2016 model years. It assigns target fuel economies to each size of vehicle (as determined by width and wheelbase), limiting the incentives for any change in fleet composition. This increases the technology costs of meeting a given target but may mitigate the safety consequences.⁸ My simulations can address these issues directly. I also plan a further separation of risk factors that will allow me to relax assumptions in the simulation model regarding the constancy of driver behavior.

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⁷ If, for example, an additional 0.9 MPG appeared through changes in technology within vehicle class, the simulation would represent a total increment of 1 MPG.

⁸ NHTSA (2008a) discusses the rationale for the footprint rule. Technology costs are higher because all improvement must be achieved through technology; without the footprint basis some of the improvement may come from technology and some via fleet composition.

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