Appendix for *The Effect of Fuel Economy Standards on Vehicle Weight Dispersion and Accident Fatalities*

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Appendix A: Further Summary Statistics

Table A1 gives the contribution of each data source to our final dataset. While Ward's has good coverage of vehicles after 1981, it has much lower coverage between 1971 and 1981, particularly for light-trucks, an no coverage before 1971. Automobile Catalogue provides data on many trims that are not found in Ward's–particularly in the period before 1981. The Automobile Catalogue data are of most value before 1978 and are especially useful in the prediction of the counterfactual fuel economy.

Table A2 presents details on the full State Data System (SDS) accident data. For each state in the datset, it should the years that are available with VINs. It provides the raw counts of accidents and fatalities, as well as the final counts of accident and fatalities after the dataset is restricted to data that is useable for the analysis. In other words, the vehicles must include the VINs and the VINs must be decodable to give us the weight. Further we restrict the sample to accidents that have only 1, 2, or 3 vehicles in the accident.

Table A3 presents further information on the SDS data and the cleaning of those data, only this time by year of the accident. It shows that most data with VINS are eliminated because they either are not for a car manufacturer, or the VIN cannot be decoded, which will include pre-1980 where VINS were not standardized. We also eliminate many vehicles that can be partially decoded but not with enough detail to allow for recovery of a vehicle weight. For example, we may be able to decode the manufacturer and class but not the model or trim.

Appendix B: Why Unconditional Quantiles?

B.1 Binning and Conditional Quantile Regression Approach

This appendix provides further intuition for the unconditional quantile regression approach by comparing it to two additional approaches: binning (kernel weighted OLS) and conditional quantile regression. In the binning approach, we perform OLS regressions on observations binned by weight. In other words, we divide up our data based on quantile of weight and run an OLS regression on each 1% (or more) sample. In the conditional quantile approach, we perform a traditional conditional quantile regression.

The fundamental intuition for using unconditional quantile regressions is that in order to understand the affect on fatalities, we are interested in how the equilibrium unconditional distribution over the entire fleet changes in response to CAFE standards. Using the binning approach or conditional quantile approach would miss important features of how the fleet adjusts.

We illustrate this intuition with a simple example with data generated from a Monte Carlo analysis. First, we generate an initial untreated population of vehicles consisting of two types: high and low. These vehicles are distributed over an outcome variable, such as weight. The vehicle type could refer to any covariate we wish to control for, such as the automaker or vehicle class. We then implement an illustrative treatment that affects only one of the two types of vehicles. Suppose the high type (e.g., luxury vehicles) is unaffected, but the low type (e.g., economy vehicles) shifts down 10 units in the outcome variable.

Panel (a) of Figure A1 illustrates this example. Each dot is a vehicle. The bottom row shows the untreated vehicles, with some overlap between the high and low types. The top row shows the vehicles after the treatment. The red dots have all been shifted left (e.g., the lighter vehicles were down-weighted). Note that within each vehicle type (i.e., conditional on vehicle type), the treatment does not generate dispersion. But the unconditional distribution does exhibit increased dispersion after the treatment.

The dotted blue lines show the unit difference between the treated and untreated populations for the 10th, 50th, and 90th unconditional quantiles of the distribution of the outcome variable. The lighter-colored line indicates the quantile after the treatment, while the darker line indicates the quantile before the treatment. Because the 10th quantile only contains the low type, it has shifted down by 10 units. The median drops by 5 units because it is a mix of the effect on the low and high types. The 90th quantile does not shift because it only contains the high type, which is unaffected by the treatment.

Panel (b) of Figure A1 shows the estimated effect of the treatment on each quantile of the outcome variable distribution using several approaches: binned OLS, conditional quantile regression, and RIF unconditional quantile regression. The estimations in all three approaches include the vehicle type as a control variable. Note that whenever there is a positive slope in this graph, there is increased dispersion. This is because the treatment reduces the outcome variable more where it is already low than where it is comparatively higher.

The binned OLS (kernel-weighted OLS) estimates are plotted in blue and suggest that treatment produces little change in the distribution except at the extreme lower quantiles. The lack of an estimated effect for most of the distribution is because all data outside of that bin are ignored. Within the bin, for most of the distribution, the treated and untreated observations have the same mean, roughly the center of the bin. This implies an estimated effect of zero.

A more interesting case are the estimates of the conditional quantile regression. Because we have conditioned on vehicle type, the plotted coefficient is the effect of treatment averaged across the high and low type. Thus we are averaging an effect of -10 for the low type and 0 for the high type resulting in a flat line at -5. The line connecting these coefficients has zero slope suggesting no change in the dispersion of the distribution (except at the very ends). In other words, *conditional* on type, there is no change to dispersion.[1]

In contrast, the RIF unconditional quantile regression presents results that describe the behavior that we are trying to capture. We see the substantial effect at the lower quantiles of the distribution of the outcome variable (e.g., a down-weighting) that one would expect based on the construction of the example, as shown in Panel (a). The top quantiles of the unconditional distribution are entirely unaffected by the treatment, and the the RIF-regression coefficients show that the top quantiles remain unaffected. The middle quantiles of the unconditional distribution are only partly affected by the treatment (there are both high and low type vehicles and only the low type is affected) and accordingly, the middle is shifted down by 5 units. The lowest quantiles are affected the most (there are only low type vehicles), and we see the lowest ones shifted down by about 10 units.

[1]This can even result in a counterintuitive result if within each *type* there is compression but across *type* there is dispersion.

This example illustrates the value in using the unconditional quantile regression approach for estimating the equilibrium change in the weight distribution for each fleet. Note that the performance of all three approaches is relatively poor at the edges. For this reason, we always omit the 3 highest and lowest quantiles in our results.

B.2 Panel Data Approach

Another potential alternative method to RIF-regression would be to build a panel dataset based on the vehicle model. This would allow us to examine within-model weight changes. Our concerns with this method are that it would involve excessive researcher discretion and would greatly reduce the size of the dataset, considerably reducing the usefulness of the analysis.

Determining when trims become separate models and what level of aggregation is needed involves considerable researcher discretion. As an example, there are cases where a model is a known successor to another (e.g., the Cadillac DTS is a known successor to the DeVille), but it has a different model name and has been changed in some ways. Thus, it is unclear if it should be counted as a continuation of the predecessor in the development of the panel. Conversely it is difficult to know if a vehicle can be redesigned to the point that, despite having the same name, it is a new model (e.g. Ford Taurus and Ford Taurus X). Even when models can cleanly be identified, the introduction and termination of models can be affected by the regulations we are studying, which would result in selection bias.

In Table A4 we present further summary statistics on the turnover in models. There is a pronounced increase in vehicle turnover in the period from 1975-1995 with more than 100 new models introduced and terminated in any 5-year window. While some of this behavior may be due to incomplete coverage of the Ward's database during this time period, inspection suggests this is not entirely a data issue. For example, many American Motors Corporation vehicles were discontinued in the late 70s and early 80s and many station wagons were also discontinued.

It is very likely that at least some of this increased turn-over was related to CAFE. In Table A5 we estimate a count model on the number of introductions and terminations on our preferred measure of CAFE stringency. Although these models are sensitive to specification, we view these results as suggestive evidence that an increase in stringency increases the turnover of light weight vehicles. In Row 1 we find that high stringency increases the introduction of new vehicle models and in Row 3 we find that high stringency increases the termination of models. Controlling for a time trend renders the results statistically insignificant. Regardless, but these regressions indicate to us that a panel of vehicle models would suffer from selection issues, and thus would be a problematic approach to estimate the effect of CAFE standards on weight.

Appendix C: Further Discussion of Stringency Measure

C.1 Alternate First Stage Regressions

The choice of variables used in predicting counterfactual fuel economy in our preferred stringency is somewhat arbitrary. Table A6 tests several other methods of predicting this stringency and shows the effects on our estimated coefficients for the domestic car fleet.

Row 1 repeats our baseline prediction method as a point of comparison. In this method fuel economy of vehicles is regressed on gasoline prices, GDP, and a trend separately by firm and fleet. Row 2 includes two additional lags of gasoline prices and GDP finding very little change in the estimated coefficients. Row 3 adds a squared trend to our baseline specification. This increases the point estimates near the median, but continues to suggest downweighting of low weight vehicles and dispersion in the domestic car fleet.

C.2 Credit Balance

C.2.1 Credit Balance as a Measure of Stringency

Another possible stringency measure is to use the CAFE credit balance. Automakers are required to meet the sales weighted average for each model year. If they are above the standard for a particular model year, they can earn "credits" that can be carried-forward. If the automaker is below the standard and does not have sufficient credits, they must either submit a plan for making up the difference within three years or pay a penalty. The major benefit of using the credit balance as a stringency measure is that it provides firm-level variation and it provides variation during the period of time after CAFE was stable. One major drawback of the credits is that the changes to credits are often very small, thus incentivizing very small changes in weight and producing large standard errors. Another drawback is that they depend on firm expectations relative to outcomes in previous years as well as expectations going forward, so the credit balance in a single year may reflect economic conditions or firm forecasts over a long period of time, rather than act as a true measure of stringency for that particular model year.

Ideally changes to the balance would be due to demand shocks that were exogenous to the firms' strategies, which may not be the case, particularly in the early days of the standard.[2] But once CAFE and gasoline prices stabilized in the 1990s there was no incentive for firms to carry large and changing balances and consequently they remained positive but close to zero.[3] Deviations from a constant balance should only have arisen from unanticipated shocks to demand. Therefore we use the credit balance after CAFE stabilized as a measure of stringency.

To construct the stringency based on credits over the previous three years, we normalize

[2]In the early days of CAFE when gasoline prices were high and firms were overshooting required targets, they amassed fairly substantial credit balances. It seems unlikely that firms were directly reacting to these amassed balances in the early days of CAFE. For this reason we remove the period before 1990 from these regressions.

[3]If demand were perfectly predictable the optimal balance would be zero but firms likely choose to carry a small positive balance due to uncertainty.

by the volume in that year, and multiply by -1.[4]

C.2.2 Results of Credit Balance Estimation

The results of this estimation are given in Table A7. Generally we find that the standard errors are too large to generate a statistically significant effect. This should not be surprising because the limited variation that there is in credit balances is from smaller decisions made by the automakers, many of which likely capture only small "tweaks" to vehicles, hence underestimating the true effect from large adjustments in the standard. Our standard controls are applied in row 1 where no coefficients are statistically significant. In row 2 we include lagged weight to consider the possibility that much of the fleet is preserved year to year and only a small portion is redesigned. In this case we find that some low quantiles indicated down-weighting and that the slope is positively sloped, indicating dispersion, for light weight vehicles. While these effects are fragile, they largely corroborate our findings using the other two measures.

Appendix D: Price Regressions

In this paper, we focused our efforts on examining the effect of CAFE stringency on vehicle weight, which differs from some of the recent literature that assumes that automakers respond to CAFE by changing relative prices. To get a sense of whether automakers have a substantial response in prices, we examine the vehicle manufacturer suggested retail price (MSRP).

In Table A8 we run a kernel-weighted OLS of MSRP on our preferred measure of stringency using a 10 quantile bandwidth with an Epanechnikov kernel. Rows 1 and 2 are run on the sample of domestic cars. We find that when stringency increases we observe price increases for the heaviest vehicles. This could possibly be due to a pricing strategy attempting to push sales away from these larger more inefficient vehicles, or it could be new technology being priced into the vehicle, which is consistent with our results showing that the automaker compliance with CAFE standards was not through the weight of the heavier vehicles. If drivers of these heavier vehicles are sensitive to attribute changes, firms may install new costly technology that improves fuel economy while preserving vehicle weight. We do not, however, observe these same dynamics for the domestic truck fleet given in rows 3 and 4. Generally these point estimates are statistically insignificant and small for all trucks.

Appendix E: Remaining Robustness Checks

Table A9 presents several key robustness checks for the domestic car fleet. Row 1 introduces lagged fleet weight to control for the fact that many vehicles are not redesigned

[4]The division by volume makes the measure comparable between large and small firms and aids in interpretation as 1 unit then represents the firm producing vehicles that are on average 1 MPG better than the CAFE level. We multiply the balance by negative one to make the sign comparable with our other measures of stringency. Thus when the balance variable is positive the standard is more binding and weight would be expected to decrease resulting in a negative coefficient.

in a given year. Row 2 includes model year fixed effects. While this regression still shows down-weighting and dispersion for low weight vehicles there is some amount of up-weighting in the middle of distribution. Because time variation is removed, this is a measure of CAFE stringency differences at the inception of CAFE, based on which manufacturers were closest or furthest from meeting the standard. Row 3 adds a quadratic trend to the regression. Row 4 uses the level of the CAFE standard as the measure of robustness. Row 5 also uses the level of the standard, but in addition includes lagged fleet weight.

Table A10 repeats these specification for the domestic truck fleet. Table A11 presents robustness checks for the Asian car fleet and Table A12 for the Asian truck fleet. Tables A13 and A14 present results for the European car and truck fleet. We generally use own stringency as these firms were not in compliance with CAFE and faced fines based on their shortfall. Some of our main checks cannot be run for these fleets because of insufficient data, or in the case of trucks because we do not have enough pre-CAFE data to generate own-fleet stringency measure. We note that for the European car fleet, increased stringency generally results in almost uniform downweighting. This is likely because all vehicles produced by these firms, including small vehicles, appeal to the same luxury demographic.

Appendix F: Details of Accident Fatality Estimation

F.1 Econometric Specifications

We estimate the effect of vehicle weight on fatality risk using a linear probability model. The exact specification is based on the number of light-duty vehicles involved. Only slightly more than 7% of all fatal crashes involve multiple fatalities. Thus, following Anderson and Auffhammer (2014) we model the probability that one or more fatalities occur in a crash. Relaxing this assumption and modeling multiple fatality accidents would very slightly increase the number of lives saved, but should not substantially change our results.

For 1-vehicle accidents, we model the probability of a fatal accident as

$$P(f_i = 1) = \beta_1 wt_i + Z_i\gamma + \varepsilon_i \tag{F.1}$$

where wt_i is the weight, in 1,000s of lbs. In our preferred specification we control for vehicle footprint (in square feet), class (using an indicator for whether the vehicle is either an SUV or van and an indicator for the vehicle being a pickup truck), the model year, a time trend, and county fixed effects. An alternative specification also includes controls for the estimated speed at the time of crash and seat belt use, but including these controls dramatically decrease the number of observations. We view this alternative specification as a useful robustness check due to the possibility that driving safer vehicles induces riskier driving behavior (Peltzman 1975).

For 2-vehicle accidents we model the probability of a fatal accident as

$$P(f_i = 1) = \beta_1 |wt_{1,i} - wt_{2,i}| + \beta_2(wt_{1,i} + wt_{2,i}) + Z_i\gamma + \varepsilon_i$$

where $wt_{j,i}$ is the weight, in 1,000s of lbs of vehicle j. The coefficient β_1 captures the effect of vehicle weight dispersion while β_2 captures the effect of the total weight involved in the crash.[5] Vector Z_i contains similar controls to the 1-vehicle crashes: the minimum and maximum vehicle footprint, minimum and maximum model year, indicators for each potential pair of car, pickup truck, and SUV/van, a dummy for any individual in any vehicle not wearing a seat belt, a variable for the sum of vehicle speeds, and a variable for the difference in vehicle speeds.

For 3-vehicle accidents we model the probability of a fatal accident as

$$P(f_i = 1) = \beta_1 sd(wt_{1,i}, wt_{2,i}, wt_{3,i}) + \beta_2(\sum_j wt_{j,i}) + Z_i\gamma + \varepsilon_i$$

where sd is the standard deviation function. Controls in Z_i include indicators for all 3-vehicle permutations of vehicle class, and the minimum and maximum across vehicles for footprint, model year, and speed. All standard errors are clustered on the county of crash.

F.1.1 Estimates of the Effect of Vehicle Weight on Fatalities

Table A15 presents the fatality regression results. Column IV is the preferred specification. Panel A presents the result for 1-vehicle crashes. The results indicate that a 1,000-pound decrease in vehicle weight will lower the probability of a fatality by 0.20%.[6] This positive relationship between fatalities and vehicle weight for 1-vehicle crashes will turn out to be important for our simulation.[7] Because CAFE lowers the mean weight of domestic vehicles in 1-vehicle crashes (about half of all crashes), this is a major force reducing fatalities.

The results also suggest that a larger footprint, newer model years, and cars (rather than trucks) all reduce fatalities. The addition of behavioral controls for speed and seat belt use do not change the results for weight but do change the results for the SUV/van indicator, likely due to a correlation between class and risky behavior.

Panels B and C present the results for 2- and 3-vehicle accidents. For both types of accidents the coefficient on total vehicle weight is roughly similar to the coefficient estimated for 1-vehicle crashes.[8] Decreasing the total weight involved in a crash decreases the number of fatalities. Increased dispersion, either measured by the absolute value of the difference in weights for 2-vehicle crashes or the standard deviation of weight for 3-vehicle crashes, increases fatalities. These two results together suggest that down-weighting low-weight vehi-

[5]Because all crashes involve two vehicles the effect of average vehicle weight can be determined by dividing β_2 by 2. We use this measure so that the effect of 1,000 lbs of down-weighting can be compared for the dispersion and mean.

[6]In appendix tables A16 through A19 we extensively test the robustness of this result and find that the coefficient is consistently positive and statistically significant. Specifically, we examine subsamples with drivers between the ages of 25 and 65 to look at driver age-vehicle choice correlation, accidents without any intoxicated drivers, only daytime crashes, urban crashes, crashes where all drivers are insured, rollovers, and non-rollovers. We also examine the probability of a driver fatality and the sensitivity of the results to state population weights. In all regressions the coefficient on vehicle weight is positive.

[7]Qualitatively similar results are shown by Anderson and Auffhammer (2014) and Jacobsen (2013) for 1-vehicle crashes. White (2004) does not control for vehicle weight but finds that light trucks are deadlier in 1-vehicle crashes, also suggesting a similar result.

[8]In appendix tables A16 through A19 we test the robustness of this result and find that the coefficient is consistently positive.

cles will both lower the total weight, reducing fatalities, and increase dispersion, increasing fatalities. The net effect on fatalities depends on the characteristics of the fleet and the effect of CAFE on the full weight distribution.

We again find that a larger footprint is generally protective to occupants in the smaller vehicle. Model year controls have negative coefficients suggesting that safety technology has improved over time. In regressions controlling for speed and seatbelts, the time trend has a negative coefficient, possibly due to the influence of policy, road design, and safety programs.

We perform extensive robustness checks on these estimation results. Tables A16 through **??** present these robustness checks. In all regressions the dependent variable is an indicator for the presence of a fatality in any vehicle. We find these to be largely confirmatory of our primary results, giving us further confidence in the primary findings that increasing dispersion increases fatalities, while reducing the mean weight reduces fatalities.

Appendix G: Counterfactual Fatalities

Table A20 shows the RIF-regression coefficients that enter the simulation. We examine three scenarios to explore the robustness of our results. In scenario 1 all coefficients are used. In scenario 2 all insignificnat coefficients are set to zero. In scenario 3 all non-Domestic (rows 3 through 6) are set to zero.

Table A21 gives more information on the relationship between vehicle footprint and vehicle weight. In all regressions the log of vehicle footprint in square feet is regressed on vehicle weight. Robustness checks include controls for horsepower and fuel economy, firm fixed effects, and model year fixed effects. We also use subsamples of the domestic firms and changes in the time frame. We adopt 0.7 as the footprint-weight elasticity used for altering footprint in our simulations based on these regressions.

Table A22 shows the coefficients of the regression that imputes the percent change in fatalities to the national level. Because our sample is relatively skewed towards Eastern and Midwestern states, some areas, such as the West, that have lower population density counties and a larger share of Asian manufactured vehicles are underrepresented. In these regressions the dependent variable is the county-level percent change in fatalities for the listed scenario in a world without CAFE. Positive coefficients indicate CAFE saves lives more in counties with that characteristic. We include county level fatalities (taken from FARS) as measure of driving intensity and dangerous behavior in a county and county level population from the U.S. Census. We also include state level values based on the NHTS 2009 survey of mean vehicle weight, fraction of vehicles that are light-duty trucks, mean vehicle age, and the fraction of the fleet in that state from Asian and Domestic manufacturers. For fatalities, population, mean vehicle weight, and age we use the Inverse Hyperbolic Sine transformation $log(y_i + (y_i^2 + 1)^{1/2})$. We use this transformation because population and fatalities are highly skewed and we would ideally use the ln transformation but some rural counties have zero fatalities. The benefit of this transformation is that it approaches the ln transformation for larger values but is also defined for zero (Burbridge et al. 1998).

	Automobile Catalog					Ward's				
	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max	N
Pre 1971	3,678.0	(491.2)	1,312.0	6,173.0	20,007					0
Cars	3,678.1	(491.8)	1,312.0	6,173.0	19,803					0
Light Trucks	3,668.0	(433.8)	2,315.0	4,696.0	204					0
1971 - 1981	3,591.0	(700.7)	1,537.0	6,041.0	10,016	3,336.5	(874.5)	1,290.0	5,783.0	2,002
Cars	3,583.2	(703.3)	1,537.0	6,041.0	9,278	3,338.8	(872.0)	1,290.0	5,783.0	1,942
Light Trucks	3,690.2	(658.7)	2,425.0	5,170.0	738	3,262.0	(958.0)	1,984.0	5,165.0	60
Post 1981	3,365.7	(830.5)	1,488.0	7,725.0	17,222	3,889.2	(1149.1)	1,048.0	8,003.0	32,887
Cars	3,057.1	(581.2)	1,488.0	4,773.0	11,880	3,107.2	(640.2)	1,488.0	6,340.0	14,727
Light Trucks	4,052.1	(888.8)	2,339.0	7,725.0	5,342	4,523.3	(1077.4)	1,048.0	8,003.0	18,160

Notes: Prediction of counterfactual fuel economy includes a trend, trend-squared, gas price, and GDP. Quantiles coefficients plotted by vehicle weight within quantile. All regressions include firm fixed effects and controls for average gas price and GDP in 3 prior years, except for regressions 2 and 4 which only include gas price and GDP in the prior year.
[a] .

Table A1: Summary Statistics on Weight (in lbs.) by Data Source

Panel A: Initial Data						
					Raw Counts[b]	
State	Years	Years with VINS[a]	County of Crash	Seatbelt and Speed	Accidents	Fatalities
Florida	95-08	95-08	Yes	Yes	3,474,433	39,848
Georgia	95-08	98-08	Partial	No	3,569,036	16,265
Illinois	95-09	95-09	Yes	No	5,504,855	18,514
Kansas	94-08	94-08	Yes	Partial	1,099,847	6,381
Michigan	95-09	04-09	Yes	No	1,979,599	6,071
Missouri	95-08	95-08	Yes	No	2,555,240	14,387
Nebraska	99-07	99, 01-07	Yes	No	535,557	2,208
New Mexico	89-10	89-99, 01-10	Yes	No	1,028,377	8,479
New York	00, 02-10	00, 02-10	Yes	No	2,901,859	12,850
North Carolina	99-08	99-08	Yes	Yes	2,718,668	14,738
Pennsylvania	89-01, 03-10	89-01, 03-10	Yes	Yes	2,849,785	29,780
Virginia	89-09	05-06, 08-09	No	Yes	410,054	2,180
Washington	89-10	02-10	Yes	No	1,130,137	4,802
Total					29,757,447	176,503

Panel B: Vehicles Usable for Regressions						
	Accidents				Fatalities	
State	With VINS	Vehicle Count 1, 2, or 3[c]	VINs Decode with Weight	Fraction of Accidents in Final Set	In Final Set	Fraction
Florida	3,384,336	3,079,875	1,731,365	0.42	14,738	0.37
Georgia	3,542,542	3,444,921	2,006,915	0.51	7,535	0.46
Illinois	5,058,120	4,879,232	2,372,437	0.35	7,037	0.38
Kansas	622,055	604,028	339,330	0.28	2,705	0.42
Michigan	1,868,712	1,816,707	1,559,079	0.72	3,179	0.52
Missouri	2,424,946	2,347,948	1,231,635	0.42	7,394	0.51
Nebraska	486,593	472,309	292,833	0.52	1,102	0.50
New Mexico	885,347	845,674	448,372	0.36	2,731	0.32
New York	2,687,175	2,471,994	2,268,631	0.66	5,665	0.44
North Carolina	2,685,769	2,543,650	2,006,645	0.68	7,556	0.51
Pennsylvania	2,841,573	2,689,781	1,835,255	0.60	15,925	0.53
Virginia	270,582	256,858	124,767	0.27	581	0.27
Washington	1,053,755	1,001,976	823,970	0.61	2,368	0.49
Total	27,811,505	26,454,953	17,041,234	0.57	78,516	0.44

Notes:
[a] Years with less than 10% VINs encoded considered missing.
[b] Sums fatalities in state years with VINs recorded in more than 10% of all accidents.
[c] Excludes motorcycles, mopeds, bicycles etc.

Table A2: State Data System Accident Data

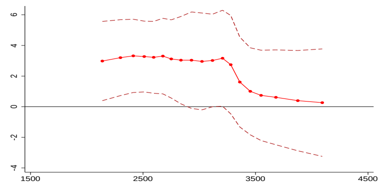
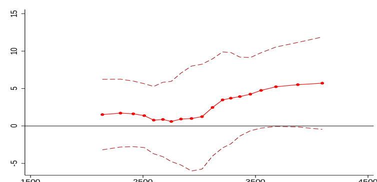
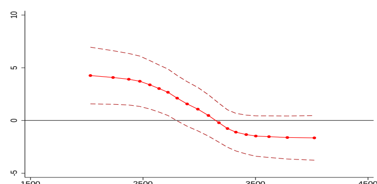
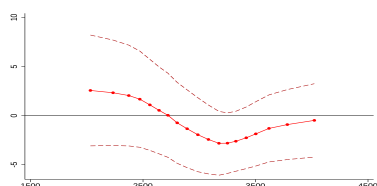
Crash Year	Number Vehicles with VINS	Not valid pattern (includes pre-1980)	Manufacturer not valid or not a car producer	No obvious VIN error but cannot be decoded (includes pre-1980)	Decoded but no weight or model year	Final Sample	Percent decoded
	I	II	III	IV	V	VI	VII
1989	331,790	121,012	23,649	4,485	9,104	173,542	52%
1990	316,690	58,232	50,810	9,426	10,555	187,673	59%
1991	293,203	43,024	45,954	8,097	10,517	185,619	63%
1992	282,721	28,092	39,375	7,010	10,194	198,054	70%
1993	280,421	27,383	32,572	5,724	10,447	204,299	73%
1994	290,207	28,950	29,631	5,255	11,271	215,103	74%
1995	1,528,744	42,535	204,530	568,351	35,683	677,656	44%
1996	1,314,078	36,812	162,605	404,301	36,636	673,732	51%
1997	1,656,068	33,653	176,088	321,916	56,141	1,068,279	65%
1998	2,101,805	34,907	197,432	396,637	73,306	1,399,536	67%
1999	2,579,049	38,478	252,407	518,227	86,940	1,683,007	65%
2000	3,264,582	38,101	226,096	440,939	126,098	2,433,365	75%
2001	2,950,756	18,589	247,046	498,333	107,206	2,079,597	70%
2002	3,439,280	19,242	257,377	566,749	122,246	2,473,679	72%
2003	3,626,438	31,939	253,657	569,679	126,408	2,644,767	73%
2004	4,119,930	33,090	264,342	489,904	142,716	3,189,889	77%
2005	4,102,153	27,145	274,913	464,934	141,095	3,194,075	78%
2006	4,095,763	22,072	250,614	419,249	140,501	3,263,329	80%
2007	4,204,760	22,904	236,524	368,493	140,959	3,435,886	82%
2008	4,192,961	29,833	225,648	354,711	138,190	3,444,583	82%
2009	2,053,501	10,609	104,742	117,169	61,084	1,759,899	86%
2010	916,523	4,299	20,873	17,491	30,588	843,275	92%

Table A3: SDS Data and Deletions by Year of Crash

	Number of Products Introduced	Number of Products Terminated
1970-1974	99	66
1975-1979	155	130
1980-1984	122	107
1985-1989	119	119
1990-1994	117	116
1995-1999	82	85
2000-2004	87	78

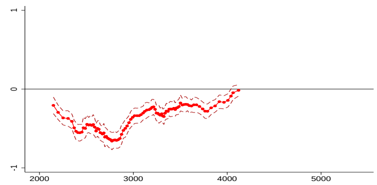
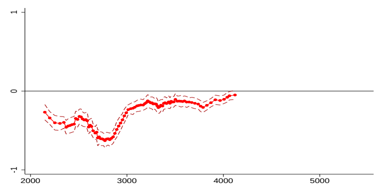
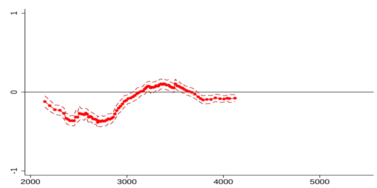
Notes: Counts any interruption as a new product. Includes all automakers.

Table A4: Model Introductions and Terminations by Year

	Coefficients	Model Years	Disp. Coeff.	Details
		Product Introduction Regressions		
1		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	Negative Binomial regression by vehicle weight quanitle using 30-quanitle bandwidth. Trends omitted.
2		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	Negative Binomial regression by vehicle weight quanitle using 30-quanitle bandwidth. Trends included.
		Product Termination Regressions		
3		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	Negative Binomial regression by vehicle weight quanitle using 30-quanitle bandwidth. Trends omitted.
4		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	Negative Binomial regression by vehicle weight quanitle using 30-quanitle bandwidth. Trends included.

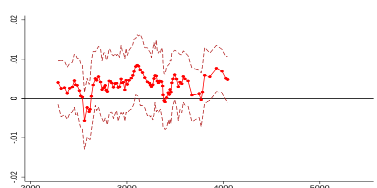
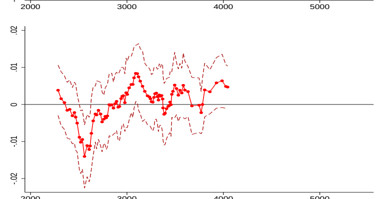
Notes: Prediction of counterfactual fuel economy includes a trend, trend-squared, gas price, and GDP. Quantiles coefficients plotted by vehicle weight within quantile. All regressions include firm fixed effects and controls for average gas price, GDP in 3 prior years, and a quadratic trend.
[c] ?

Table A5: Introductions and Terminations, Domestic Cars

	Coefficients	Model Years	Disp. Coeff.	Details
		COUNTERFACTUAL FUEL ECONOMY		
1		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	Base Specification: Counterfactual fuel economy predicted from a trend, GP_t, and GDP_t
2		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	Counterfactual fuel economy predicted from a trend, GP_t, GP_{t-1}, GP_{t-2}, GDP_t, GDP_{t-1} and GDP_{t-2}
3		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	Counterfactual fuel economy predicted from a trend, trend-squared, GP_t, and GDP_t

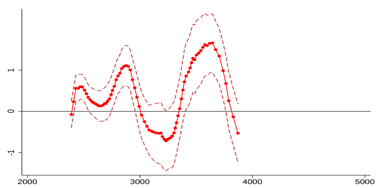
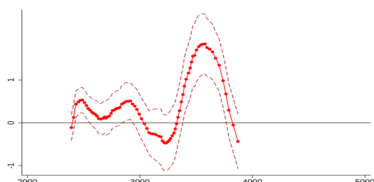
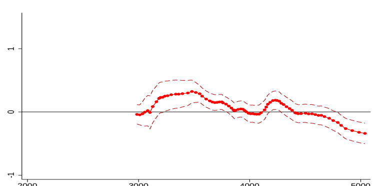
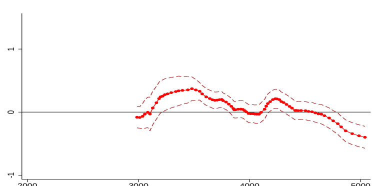
Notes: All regressions include firm fixed effects and controls for average gas price, GDP in 3 prior years, and a quadratic trend.

Table A6: Alternate 1st Stage Prediction, Domestic Cars

	Coefficients	Model Years	Displayed Coefficient	Gas Price	GDP	Firm Specf. Quadratic	Lagged Fleet Weight	Model Year F.E
		THREE YEAR CREDIT BALANCE						
1		1990-2000	Credit Balance	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	No	No
2		1990-2000	Credit Balance	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	Yes	No

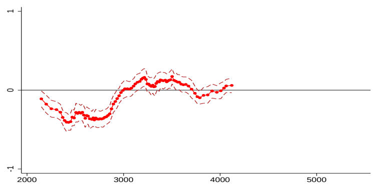
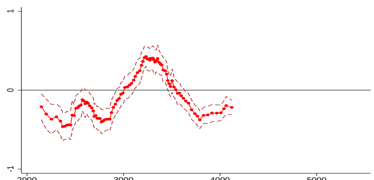
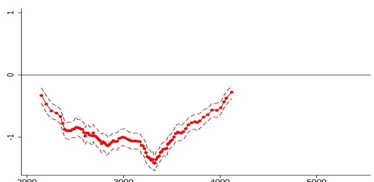
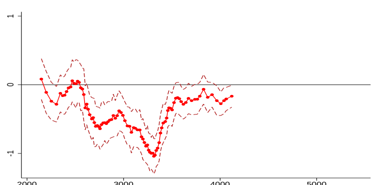
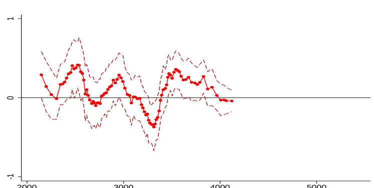
Notes: Credit balance is summed over the previous three years, normalize by the volume in the last year, and multiply by -1 to make interpretation similar to that of the prior stringency methods.

Table A7: Cumulative 3-year Credit Balance, Domestic Cars

	Coefficients	Model Years	Displayed Coefficient	Gas Price	GDP
		CARS			
1		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$
2		1978-2005	S_{t-1}	$l(GP_{t-1})$	$l(GDP_{t-1})$
		TRUCKS			
3		1978-2000	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$
4		1978-2005	S_{t-1}	$l(GP_{t-1})$	$l(GDP_{t-1})$

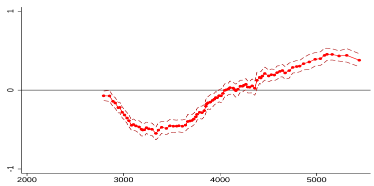
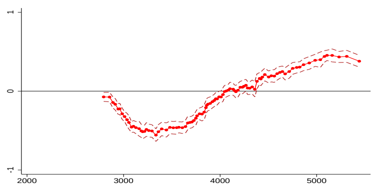
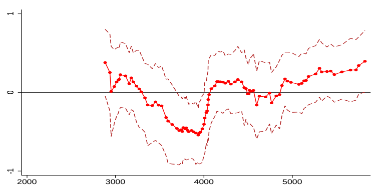
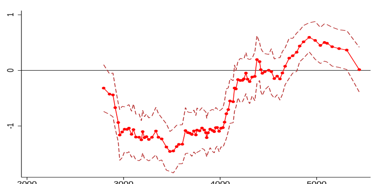
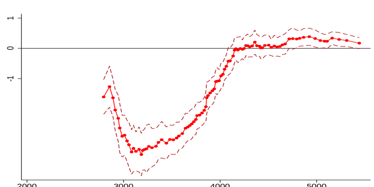
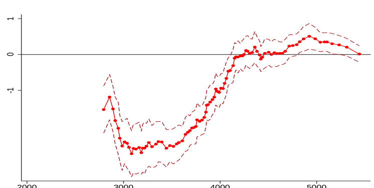
Notes: Prediction of counterfactual fuel economy includes a trend, trend-squared, gas price, and GDP. Quantiles coefficients plotted by vehicle weight within quantile. All regressions include firm fixed effects and controls for average gas price, GDP in 3 prior years, and a quadratic trend.
[c] ?

Table A8: Prices, Domestic

	Coefficients	Model Years	Displayed Coefficient	Gas Price	GDP	Firm Specf. Quadratic	Lagged Fleet Weight	Model Year F.E
		Counterfactual Fuel Economy						
1		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	Yes	No
2		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	No	Yes
3		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	Yes	No	No
		CAFE Standard						
4		1978-2005	$l(CAFE_t)$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	No	No
5		1978-2005	$l(CAFE_t)$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	Yes	No

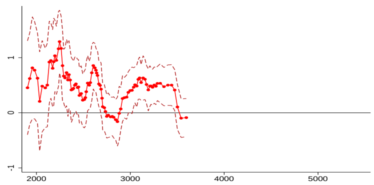
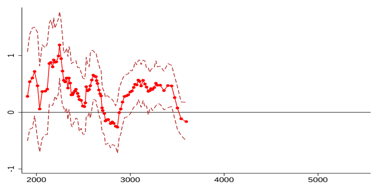
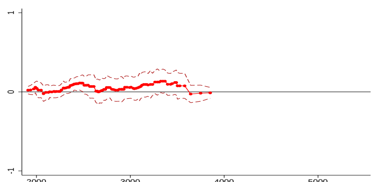
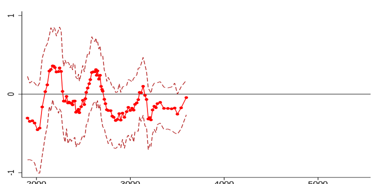
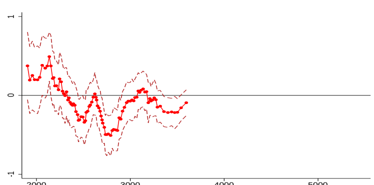
Notes: Prediction of counterfactual fuel economy includes a trend, trend-squared, gas price, and GDP. Quantiles coefficients plotted by vehicle weight within quantile. All regressions include firm fixed effects and controls for average gas price, GDP in 3 prior years, and a quadratic trend.

Table A9: Specification Robustness, Domestic Cars

	Coefficients	Model Years	Displayed Coefficient	Gas Price	GDP	Sales Weighted	Lagged Fleet Weight	Firm Specf. Quad.
		Counterfactual Fuel Economy						
1		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	No	No
2		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	Yes	No
3		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	Yes	No	No
4		1978-2005	$\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	No	Yes
		CAFE Standard						
5		1978-2005	$l(CAFE_t)$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	No	No
6		1978-2005	$l(CAFE_t)$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	Yes	No

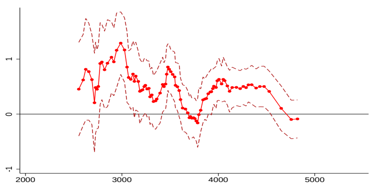
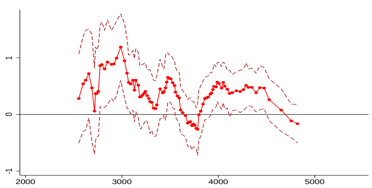
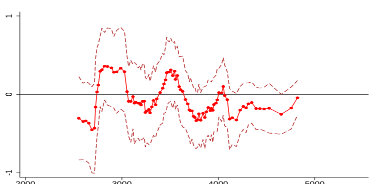
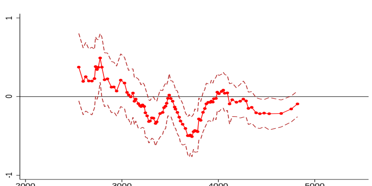
Notes: Prediction of counterfactual fuel economy includes a trend, trend-squared, gas price, and GDP. Quantiles coefficients plotted by vehicle weight within quantile. All regressions include firm fixed effects and controls for average gas price, GDP in 3 prior years, and a quadratic trend.

Table A10: Domestic Trucks

	Coefficients	Model Years	Displayed Coefficient	Gas Price	GDP	Sales Weighted	Lagged Fleet Weight
			Counterfactual Fuel Economy				
1		1978-2005	US $\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	No
2		1978-2005	US $\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	Yes
3		1978-2005	US $\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	Yes	No
			CAFE Standard				
4		1978-2005	$l(CAFE_t)$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	No
5		1978-2005	$l(CAFE_t)$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	Yes

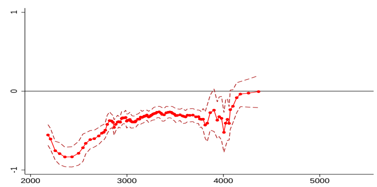
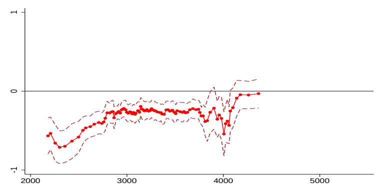
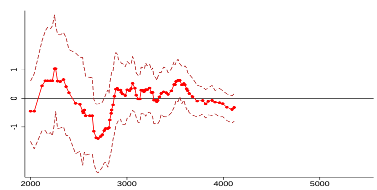
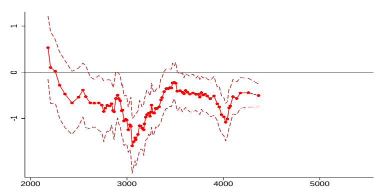
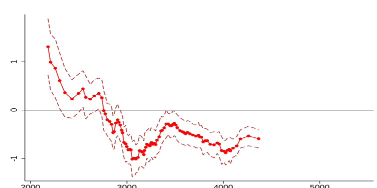
Notes: Prediction of counterfactual fuel economy includes a trend, trend-squared, gas price, and GDP. Quantiles coefficients plotted by vehicle weight within quantile. All regressions include firm fixed effects and controls for average gas price, GDP in 3 prior years, and a quadratic trend.
[c] ?

Table A11: Asian Cars

	Coefficients	Model Years	Displayed Coefficient	Gas Price	GDP	Sales Weighted	Lagged Fleet Weight
		COUNTERFACTUAL FUEL ECONOMY					
1		1978-2005	US $\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	No
2		1978-2005	US $\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	Yes
3	Insufficient Sales Data	1978-2005	US $\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	Yes	No
		CAFE STANDARD					
4		1978-2005	$l(CAFE_t)$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	No
5		1978-2005	$l(CAFE_t)$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	Yes

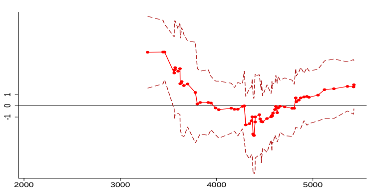
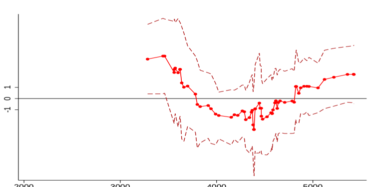
Notes: Prediction of counterfactual fuel economy includes a trend, trend-squared, gas price, and GDP. Quantiles coefficients plotted by vehicle weight within quantile. All regressions include firm fixed effects and controls for average gas price, GDP in 3 prior years, and a quadratic trend.

Table A12: Asian Trucks

	Coefficients	Model Years	Displayed Coefficient	Gas Price	GDP	Sales Weighted	Lagged Fleet Weight
			Counterfactual Fuel Economy				
1		1978-2005	Own $\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	No
2		1978-2005	Own $\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	Yes
3		1978-2005	Own $\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	Yes	No
			CAFE Standard				
4		1978-2005	$l(CAFE_t)$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	No
5		1978-2005	$l(CAFE_t)$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	Yes

Notes: Prediction of counterfactual fuel economy includes a trend, trend-squared, gas price, and GDP. Quantiles coefficients plotted by vehicle weight within quantile. All regressions include firm fixed effects and controls for average gas price, GDP in 3 prior years, and a quadratic trend.

Table A13: European Cars

	Coefficients	Model Years	Displayed Coefficient	Gas Price	GDP	Sales Weighted	Lagged Fleet Weight
			COUNTERFACTUAL FUEL ECONOMY				
1	No pre-CAFE data.	1978-2005	Own $\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	No
2	No pre-CAFE data.	1978-2005	Own $\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	Yes
3	No pre-CAFE data.	1978-2005	Own $\frac{\sum_{i=-1}^{3} S_{t-i}}{5}$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	Yes	No
			CAFE STANDARD				
4		1978-2005	$l(CAFE_t)$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	No
5		1978-2005	$l(CAFE_t)$	$l(\frac{\sum_{i=1}^{3} GP_{t-i}}{3})$	$l(\frac{\sum_{i=1}^{3} GDP_{t-i}}{3})$	No	Yes

Notes: Prediction of counterfactual fuel economy includes a trend, trend-squared, gas price, and GDP. Quantiles coefficients plotted by vehicle weight within quantile. All regressions include firm fixed effects and controls for average gas price, GDP in 3 prior years, and a quadratic trend.
[c] ?

Table A14: European Trucks

Panel A: One Vehicle Crashes	I	II	III	IV	V
Weight (1000 lbs)	-0.00015***	0.00126***	0.00201***	0.00200***	0.00249***
	(0.00006)	(0.00012)	(0.00012)	(0.00012)	(0.00030)
Pickup Truck	0.00196***	0.00296***	0.00259***	0.00260***	0.00199***
	(0.00015)	(0.00019)	(0.00018)	(0.00018)	(0.00036)
Van or SUV	0.00086***	-0.00011	-0.00040***	-0.00039***	0.00084**
	(0.00014)	(0.00013)	(0.00013)	(0.00013)	(0.00033)
Footprint		-0.00005***	-0.00005***	-0.00005***	-0.00004***
		(0.00000)	(0.00000)	(0.00000)	(0.00001)
Model Year			-0.00024***	-0.00026***	-0.00006**
			(0.00001)	(0.00001)	(0.00002)
Trend				0.00006**	-0.00036***
				(0.00002)	(0.00005)
County fixed effects	Y	Y	Y	Y	Y
Controls for Speed and Seatbelts	N	N	N	N	Y
N	7,345,248	7,345,248	7,345,202	7,345,202	1,639,271

Panel B: Two Vehicle Crashes	I	II	III	IV	V
Abs(Weight Difference) (in 1000s)	0.00068***	0.00057***	0.00056***	0.00056***	0.00059***
	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.00011)
Sum of Vehicle Weights	0.00003	-0.00002	0.00021***	0.00021***	0.00038***
	(0.00003)	(0.00004)	(0.00004)	(0.00004)	(0.00011)
	(0.00010)	(0.00011)	(0.00011)	(0.00011)	(0.00026)
Footprint of Smallest Vehicle		-0.00000**	-0.00001***	-0.00001***	-0.00001*
		(0.00000)	(0.00000)	(0.00000)	(0.00000)
Footprint of Largest Vehicle		0.00001***	0.00000**	0.00000**	0.00000
		(0.00000)	(0.00000)	(0.00000)	(0.00000)
Oldest Model Year			-0.00005***	-0.00005***	0.00002
			(0.00001)	(0.00001)	(0.00001)
Youngest Model Year			-0.00005***	-0.00005***	-0.00001
			(0.00001)	(0.00001)	(0.00001)
Trend				0.00001	-0.00015***
				(0.00001)	(0.00003)
County fixed effects	Y	Y	Y	Y	Y
Class Dummies[a]	Y	Y	Y	Y	Y
Controls for Speed and Seat belts	N	N	N	N	Y
N	8,956,966	8,956,966	8,956,966	8,956,966	2,125,543

Panel C: Three Vehicle Crashes	I	II	III	IV	V
Std. Dev. of Weights	0.00191***	0.00133***	0.00128***	0.00128***	0.00192**
	(0.00029)	(0.00034)	(0.00034)	(0.00034)	(0.00078)
Sum of Weights	0.00025***	0.00023**	0.00049***	0.00049***	0.00058**
	(0.00009)	(0.00012)	(0.00013)	(0.00012)	(0.00028)
Footprint of Smallest Vehicle		-0.00002**	-0.00002**	-0.00002**	-0.00001
		(0.00001)	(0.00001)	(0.00001)	(0.00002)
Footprint of Largest Vehicle		0.00001***	0.00001**	0.00001**	-0.00001
		(0.00000)	(0.00000)	(0.00000)	(0.00001)
Oldest Model Year			-0.00012***	-0.00012***	-0.00008
			(0.00002)	(0.00002)	(0.00005)
Youngest Model Year			-0.00003	-0.00003	0.00002
			(0.00003)	(0.00003)	(0.00009)
Trend				-0.00001	-0.00022**
				(0.00004)	(0.00009)
County fixed effects	Y	Y	Y	Y	Y
Class Dummies[a]	Y	Y	Y	Y	Y
Controls for Speed and Seatbelts	N	N	N	N	Y
N	739,020	739,020	739,020	739,020	190,249

Notes: Standard errors in parentheses clustered at the county level with * indicating significance at 5%, ** at 1%, and *** at >1%.

[a] Dummies for all combinations of Car, Van/SUV, and Pickup Truck. Two car or three car accidents omitted.

Table A15: Accident Regressions

Panel A: One Vehicle Crashes						
				Central		
	I	II	III	IV	V	VI
Weight	-0.00015***	0.00126***	0.00201***	0.00200***	0.00199***	0.00248***
	(0.00006)	(0.00012)	(0.00012)	(0.00012)	(0.00012)	(0.00030)
Footprint		-0.00005***	-0.00005***	-0.00005***	-0.00005***	-0.00004***
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)
Height					0.00000	0.00001
					(0.00001)	(0.00001)
Constant	0.00676***	0.00869***	0.47936***	0.40429***	0.40537***	0.83086***
	(0.00017)	(0.00021)	(0.02257)	(0.04445)	(0.04445)	(0.07864)
R-squared	0.00	0.00	0.01	0.01	0.01	0.06
N	7345248	7345248	7345202	7345202	7345202	1639271
Panel B: Two Vehicle Crashes						
	I	II	III	IV	V	VI
Abs(weight1-weight2)	0.00068***	0.00057***	0.00056***	0.00056***	0.00053***	0.00057***
	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.00011)
Sum of vehicle weights	0.00003	-0.00002	0.00021***	0.00021***	0.00018***	0.00037***
	(0.00003)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00011)
Footprint Smallest Veh.		-0.00000**	-0.00001***	-0.00001***	-0.00000***	-0.00001*
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Footprint Largest Veh.		0.00001***	0.00000**	0.00000**	0.00000*	0.00000
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Height Smallest					-0.00001***	0.00000
					(0.00000)	(0.00001)
Height Largest					0.00002***	0.00001
					(0.00001)	(0.00002)
Constant	0.00193***	0.00194***	0.20746***	0.19839***	0.19605***	0.27203***
	(0.00017)	(0.00019)	(0.01442)	(0.01965)	(0.01972)	(0.05770)
R-squared	0.00	0.00	0.00	0.00	0.00	0.02
N	8956966	8956966	8956966	8956966	8956966	2125543
Panel C: Three Vehicle Crashes						
Three Vehicle Crashes	I	II	III	IV	V	VI
Standard Dev of Weight	0.00191***	0.00133***	0.00128***	0.00128***	0.00109***	0.00187**
	(0.00029)	(0.00034)	(0.00034)	(0.00034)	(0.00036)	(0.00080)
Sum of Weight	0.00025***	0.00023**	0.00049***	0.00049***	0.00044***	0.00058**
	(0.00009)	(0.00012)	(0.00013)	(0.00012)	(0.00013)	(0.00028)
Footprint Smallest Veh.		-0.00002**	-0.00002**	-0.00002**	-0.00002**	-0.00001
		(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00002)
Footprint Largest Veh.		0.00001***	0.00001**	0.00001**	0.00001*	-0.00001
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)
Minimum Vehicle Height					0.00000	0.00001
					(0.00001)	(0.00002)
Maximum Vehicle Height					0.00005*	0.00001
					(0.00003)	(0.00005)
Constant	0.00064	0.00116	0.30268***	0.30680***	0.31190***	0.55377***
	(0.00079)	(0.00093)	(0.04755)	(0.05534)	(0.05534)	(0.11636)
R-squared	0.01	0.01	0.01	0.01	0.01	0.03
N	739020	739020	739020	739020	739020	190249
Dependent Variable	Any Fatalities	Any Fatalities	Any Fatalities	Any Fatalities	Any Fatalities	Any Fatalities
Sample Restriction	-	-	-	-	-	-
County Fixed Effects	Y	Y	Y	Y	Y	Y
Class pair fixed effects	Y	Y	Y	Y	Y	Y
Model year of vehicles	N	N	Y	Y	Y	Y
Trend	N	N	N	Y	Y	Y
Speed and Seatbelt use	N	N	N	N	N	Y
Driver Ages	N	N	N	N	N	N
Driver Gender	N	N	N	N	N	N
Sample Weights	None	None	None	None	None	None

Notes: Linear probability model estimates of a vehicle fatality on the listed regressands. Standard errors, clustered on county, are given in parentheses with * indicating significance at 5%, ** at 1%, and *** at >1%.

Table A16: Probability of Fatality, Robustness 1

Panel A: One Vehicle Crashes						
				Central		
	I	II	III	IV	V	VI
Weight	0.00166***	0.00216***	0.00106***	0.00846***	0.00117***	0.00283***
	(0.00011)	(0.00017)	(0.00012)	(0.00098)	(0.00014)	(0.00018)
Footprint	-0.00004***	-0.00006***	-0.00003***	-0.00018***	-0.00003***	-0.00007***
	(0.00000)	(0.00000)	(0.00000)	(0.00002)	(0.00000)	(0.00000)
Height	-0.00000	0.00001	0.00001	0.00005	0.00001	-0.00001
	(0.00001)	(0.00001)	(0.00001)	(0.00004)	(0.00001)	(0.00001)
Constant	0.17219***	0.42403***	0.01042	0.02628	0.31283***	0.51471***
	(0.02643)	(0.05348)	(0.03647)	(0.33046)	(0.05008)	(0.04918)
R-squared	0.00	0.01	0.00	0.01	0.01	0.01
N	7106363	2636913	4044005	319297	3442459	3442001
Panel B: Two Vehicle Crashes						
	I	II	III	IV	V	VI
Abs(weight1-weight2)	0.00048***	0.00063***	0.00034***	0.00252***	0.00044***	0.00082***
	(0.00004)	(0.00007)	(0.00005)	(0.00061)	(0.00005)	(0.00012)
Sum of vehicle weights	0.00010***	0.00003	0.00010**	0.00044	0.00009**	0.00044***
	(0.00004)	(0.00007)	(0.00004)	(0.00058)	(0.00004)	(0.00013)
Footprint Smallest Veh.	-0.00000**	-0.00001***	-0.00000	-0.00005**	0.00000	-0.00002***
	(0.00000)	(0.00000)	(0.00000)	(0.00002)	(0.00000)	(0.00001)
Footprint Largest Veh.	0.00000	0.00001***	0.00000***	0.00001	0.00000***	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00002)	(0.00000)	(0.00000)
Height Smallest	-0.00001**	-0.00001	-0.00001**	0.00003	-0.00001**	-0.00002*
	(0.00000)	(0.00001)	(0.00000)	(0.00004)	(0.00000)	(0.00001)
Height Largest	0.00002***	0.00001	0.00001	0.00022***	0.00002***	0.00004**
	(0.00001)	(0.00001)	(0.00001)	(0.00008)	(0.00001)	(0.00002)
Constant	0.11511***	0.14899***	0.15234***	0.65907***	0.17829***	0.28384***
	(0.01474)	(0.02536)	(0.02439)	(0.24473)	(0.01881)	(0.04021)
R-squared	0.00	0.00	0.00	0.02	0.00	0.01
N	8823912	2940398	5497097	209615	6614164	2037637
Panel C: Three Vehicle Crashes						
	I	II	III	IV	V	VI
Standard Dev of Weight	0.00078***	0.00118**	0.00126***	0.00689	0.00083**	0.00170*
	(0.00029)	(0.00057)	(0.00042)	(0.00464)	(0.00036)	(0.00089)
Sum of Weight	0.00029**	0.00029	0.00038**	0.00056	0.00040***	0.00056
	(0.00011)	(0.00023)	(0.00015)	(0.00163)	(0.00013)	(0.00035)
Footprint Smallest Veh.	-0.00001**	-0.00002	-0.00001	0.00000	-0.00001	-0.00003
	(0.00001)	(0.00002)	(0.00001)	(0.00011)	(0.00001)	(0.00002)
Footprint Largest Veh.	0.00000	0.00000	0.00000	0.00007	0.00001*	0.00001
	(0.00000)	(0.00001)	(0.00001)	(0.00006)	(0.00001)	(0.00001)
Minimum Vehicle Height	-0.00000	-0.00001	-0.00000	0.00017	-0.00000	0.00003
	(0.00001)	(0.00002)	(0.00001)	(0.00013)	(0.00001)	(0.00003)
Maximum Vehicle Height	0.00005**	0.00000	0.00002	-0.00003	0.00005*	0.00005
	(0.00002)	(0.00005)	(0.00003)	(0.00035)	(0.00003)	(0.00007)
Constant	0.17383***	0.31190***	0.21380**	0.28407***	0.31578	0.23932***
	(0.04304)	(0.05534)	(0.08806)	(0.07386)	(0.69783)	(0.05550)
R-squared	0.01	0.01	0.03	0.01	0.07	0.01
N	729960	739020	192067	406742	20779	558171
Dependent Variable	Driver Fatality	Any Fatalities	Any Fatalities	Any Fatalities	Any Fatalities	Any Fatalities
Sample Restriction	-	All drivers 25 to 65	No intox'ed drivers	At least 1 intox'ed driver	Daytime Crash	Night or dusk
County Fixed Effects	Y	Y	Y	Y	Y	Y
Class pair fixed effects	Y	Y	Y	Y	Y	Y
Model year of vehicles	Y	Y	Y	Y	Y	Y
Trend	Y	Y	Y	Y	Y	Y
Speed and Seatbelt use	N	N	N	N	N	N
Driver Ages	N	N	N	N	N	N
Driver Gender	N	N	N	N	N	N
Sample Weights	None	None	None	None	None	None

Notes: Linear probability model estimates of a vehicle fatality on the listed regressands. Standard errors, clustered on county, are given in parentheses with * indicating significance at 5%, ** at 1%, and *** at >1%.

Table A17: Probability of Fatality, Robustness 2

Panel A: One Vehicle Crashes						
				Central		
	I	II	III	IV	V	VI
Weight	0.00269***	0.00124***	0.00263***	0.00232***	0.00190***	0.00165***
	(0.00023)	(0.00022)	(0.00024)	(0.00014)	(0.00014)	(0.00012)
Footprint	-0.00007***	-0.00003***	-0.00005***	-0.00006***	-0.00006***	-0.00005***
	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00000)
Height	0.00000	0.00000	-0.00001	0.00000	-0.00000	-0.00000
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Constant	0.53028***	0.26372***	0.42974***	0.44642***	0.37947***	0.34715***
	(0.07042)	(0.09389)	(0.06476)	(0.05297)	(0.05345)	(0.04584)
R-squared	0.01	0.00	0.00	0.01	0.01	0.01
N	2120946	1924517	2363459	5778799	5672921	6977006
Panel B: Two Vehicle Crashes						
	I	II	III	IV	V	VI
Abs(weight1-weight2)	0.00170***	0.00025***	0.00069***	0.00057***	0.00060***	0.00056***
	(0.00022)	(0.00005)	(0.00009)	(0.00006)	(0.00006)	(0.00005)
Sum of vehicle weights	0.00046**	0.00017***	0.00028***	0.00012**	0.00002	0.00009**
	(0.00019)	(0.00005)	(0.00008)	(0.00005)	(0.00005)	(0.00004)
Footprint Smallest Veh.	-0.00001	-0.00000	-0.00001*	-0.00001***	-0.00000***	-0.00000
	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Footprint Largest Veh.	0.00001	-0.00000	0.00000	0.00000	0.00000	0.00000*
	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Height Smallest	-0.00002	-0.00000	-0.00001*	-0.00001***	-0.00001***	-0.00001**
	(0.00001)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00000)
Height Largest	0.00003	0.00001	0.00002*	0.00003***	0.00002***	0.00001**
	(0.00003)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Constant	0.48662***	0.04930**	0.18183***	0.20006***	0.16814***	0.16043***
	(0.08561)	(0.02299)	(0.03087)	(0.02065)	(0.02000)	(0.01922)
R-squared	0.01	0.00	0.00	0.00	0.00	0.00
N	1181874	3372888	3328064	7957667	7957667	8820678
Panel C: Three Vehicle Crashes						
Three Vehicle Crashes	I	II	III	IV	V	VI
Standard Dev of Weight	0.00036	0.00066	0.00057	0.00132***	0.00142***	0.00118***
	(0.00041)	(0.00144)	(0.00058)	(0.00037)	(0.00037)	(0.00036)
Sum of Weight	0.00033**	0.00129**	0.00072***	0.00031**	0.00020	0.00035***
	(0.00014)	(0.00054)	(0.00022)	(0.00013)	(0.00013)	(0.00012)
Footprint Smallest Veh.	-0.00001	-0.00007**	-0.00003**	-0.00002**	-0.00002*	-0.00001*
	(0.00001)	(0.00003)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Footprint Largest Veh.	-0.00000	0.00003*	0.00001	0.00001	0.00001	0.00001
	(0.00001)	(0.00002)	(0.00001)	(0.00001)	(0.00001)	(0.00000)
Minimum Vehicle Height	0.00001	0.00003	0.00000	-0.00000	-0.00000	0.00000
	(0.00001)	(0.00004)	(0.00002)	(0.00001)	(0.00001)	(0.00001)
Maximum Vehicle Height	0.00006*	0.00002	0.00008**	0.00005*	0.00003	0.00004
	(0.00003)	(0.00011)	(0.00004)	(0.00003)	(0.00003)	(0.00003)
Constant	0.88437***	0.88437***	0.33364***	0.28686***	0.25475***	0.26617***
	(0.21938)	(0.21938)	(0.07465)	(0.06048)	(0.06085)	(0.05527)
R-squared	0.03	0.03	0.01	0.01	0.01	0.01
N	105821	105821	304591	648665	648665	739020
Dependent Variable	Any Fatalities	Any Fatalities	Any Fatalities	Any Fatalities	Any Fatalities	Any Fatalities
Sample Restriction	Rural Crash	Urban Crash	All drivers insured	-	-	-
County Fixed Effects	Y	Y	Y	Y	Y	Y
Class pair fixed effects	Y	Y	Y	Y	Y	Y
Model year of vehicles	Y	Y	Y	Y	Y	Y
Trend	Y	Y	Y	Y	Y	Y
Speed and Seatbelt use	N	N	N	N	N	N
Driver Ages	N	N	N	Y	Y	N
Driver Gender	N	N	N	N	Y	Y
Sample Weights	None	None	None	None	None	None

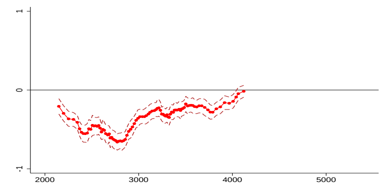
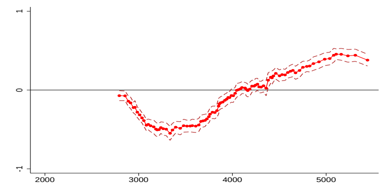
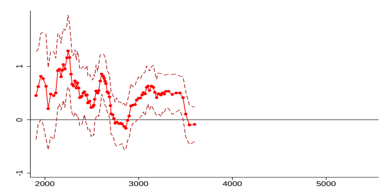
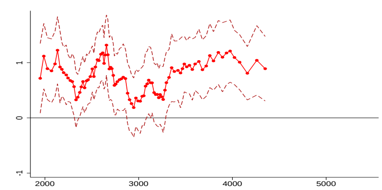
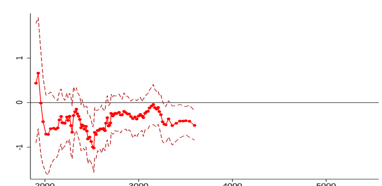
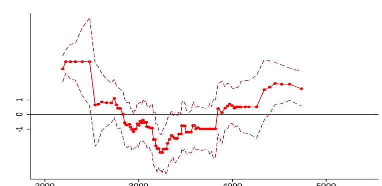
Notes: Linear probability model estimates of a vehicle fatality on the listed regressands. Standard errors, clustered on county, are given in parentheses with * indicating significance at 5%, ** at 1%, and *** at >1%.

Table A18: Probability of Fatality, Robustness 3

Panel A: One Vehicle Crashes					
				Central	
	I	II	III	IV	V
Weight	0.00236***	0.00189***	0.00204***	0.00746***	0.00180***
	(0.00029)	(0.00014)	(0.00014)	(0.00077)	(0.00015)
Footprint	-0.00004***	-0.00005***	-0.00005***	-0.00004**	-0.00004***
	(0.00001)	(0.00000)	(0.00000)	(0.00002)	(0.00000)
Height	0.00001	0.00002**	0.00000	-0.00005	-0.00001
	(0.00001)	(0.00001)	(0.00001)	(0.00004)	(0.00001)
Constant	0.81619***	0.38708***	0.42077***	0.68131***	0.54847***
	(0.07737)	(0.07254)	(0.04447)	(0.16974)	(0.04219)
R-squared	0.06	0.01	0.01	0.01	0.00
N	1637448	7345202	7345202	348927	3429657
Panel B: Two Vehicle Crashes					
	I	II	III		
Abs(weight1-weight2)	0.00063***	0.00060***	0.00055***		
	(0.00012)	(0.00006)	(0.00006)		
Sum of vehicle weights	0.00028***	0.00018***	0.00020***		
	(0.00011)	(0.00006)	(0.00005)		
Footprint Smallest Veh.	-0.00001	-0.00000	-0.00001***		
	(0.00000)	(0.00000)	(0.00000)		
Footprint Largest Veh.	0.00000	0.00000	0.00000*		
	(0.00000)	(0.00000)	(0.00000)		
Height Smallest	-0.00000	-0.00000	-0.00001		
	(0.00001)	(0.00001)	(0.00001)		
Height Largest	0.00002	0.00003***	0.00002***		
	(0.00002)	(0.00001)	(0.00001)		
Constant	0.33516***	0.17214***	0.22062***		
	(0.06458)	(0.02228)	(0.02266)		
R-squared	0.02	0.00	0.00		
N	2119959	8956966	8956966		
Panel C: Three Vehicle Crashes					
Three Vehicle Crashes	I	II	III		
Standard Dev of Weight	0.00192**	0.00106**	0.00098**		
	(0.00080)	(0.00045)	(0.00039)		
Sum of Weight	0.00052*	0.00029*	0.00040***		
	(0.00028)	(0.00015)	(0.00013)		
Footprint Smallest Veh.	-0.00001	-0.00000	-0.00001		
	(0.00002)	(0.00001)	(0.00001)		
Footprint Largest Veh.	-0.00001	0.00001*	0.00001*		
	(0.00001)	(0.00001)	(0.00001)		
Minimum Vehicle Height	0.00001	0.00000	-0.00000		
	(0.00002)	(0.00002)	(0.00002)		
Maximum Vehicle Height	0.00000	0.00004	0.00004		
	(0.00005)	(0.00003)	(0.00003)		
Constant	0.53876***	0.20086***	0.30793***		
	(0.11571)	(0.07413)	(0.05499)		
R-squared	0.03	0.03	0.01		
N	190249	739020	739020		
Dependent Variable	Any Fatalities	Any Fatalities	Any Fatalities	Any Fatalities	Any Fatalities
Sample Restriction	-	-	-	Roll Overs	Non-Roll Overs
County Fixed Effects	Y	Y	Y	Y	Y
Class pair fixed effects	Y	Y	Y	Y	Y
Model year of vehicles	Y	Y	Y	Y	Y
Trend	Y	Y	Y	Y	Y
Speed and Seatbelt use	Y	N	N	N	N
Driver Ages	N	N	N	N	N
Driver Gender	Y	N	N	N	N
Sample Weights	None	Equal State Weights	State Pop. Weights	None	None

Notes: Linear probability model estimates of a vehicle fatality on the listed regressands. Standard errors, clustered on county, are given in parentheses with * indicating significance at 5%, ** at 1%, and *** at >1%.

Table A19: Probability of Fatality, Robustness 4

	Coefficients	Segment	Model Years	Displayed Coefficient	Sales Weighted
				Domestic Firms	
1		Cars	1978-2005	Own $\frac{\sum_{i=-1}^{3} s_{t-i}}{5}$	No
2		Trucks	1978-2005	Own $\frac{\sum_{i=-1}^{3} s_{t-i}}{5}$	No
				Asian Firms	
3		Cars	1978-2005	US $\frac{\sum_{i=-1}^{3} s_{t-i}}{5}$	No
4		Trucks	1978-2005	US $\frac{\sum_{i=-1}^{3} s_{t-i}}{5}$	No
				European Firms	
5		Cars	1978-2005	US $\frac{\sum_{i=-1}^{3} s_{t-i}}{5}$	No
6		Trucks	1978-2005	US $\frac{\sum_{i=-1}^{3} s_{t-i}}{5}$	No

Notes: Prediction of counterfactual fuel economy includes a trend, trend-squared, gas price, and GDP. Quantiles coefficients plotted by vehicle weight within quantile. All regressions include firm fixed effects and controls for average gas price, GDP in 3 prior years, and a quadratic trend.

Table A20: RIF Regressions Used in Counterfactual Simulations

	I	II	III	IV	V
log(weight)	0.656***	0.727***	0.876***	0.825***	0.668***
	(0.031)	(0.079)	(0.082)	(0.100)	(0.068)
log(horsepower)		-0.072**	-0.099	-0.062*	-0.080***
		(0.027)	(0.039)	(0.031)	(0.026)
log(M.P.G.)		0.034	0.090	0.111	-0.000
		(0.062)	(0.119)	(0.075)	(0.058)
Constant	-0.364	-0.781	-1.856	-1.800*	-0.165
	(0.236)	(0.805)	(1.180)	(1.016)	(0.704)
Automaker FE	N	Y	Y	Y	Y
Model Year FE	N	Y	Y	Y	Y
US only	N	Y	N	N	N
Years	1978-2005	1978-2005	1978-2005	1995-2005	1978-1995
R-squared	0.59	0.66	0.60	0.61	0.67
N	21227	20672	11727	10917	10627

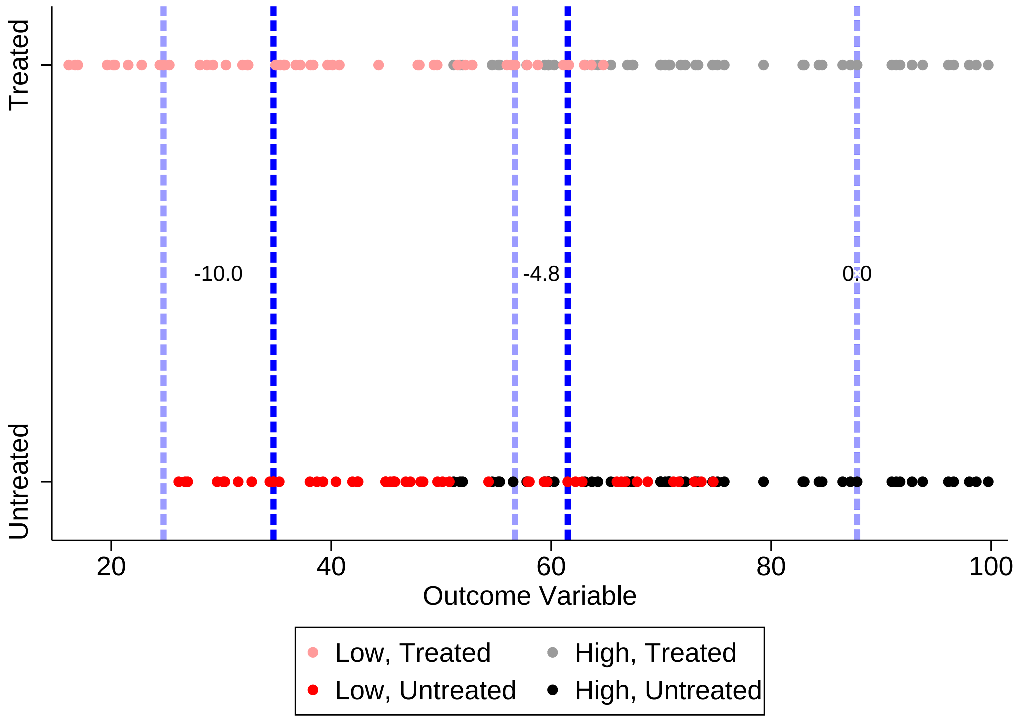
Notes: Depedent Variable Log(Footprint). Standard errors, clustered on automaker, are given in parentheses with * indicating significance at 5%, ** at 1%, and *** at >1%.

Table A21: Footprint Versus Vehicle Weight

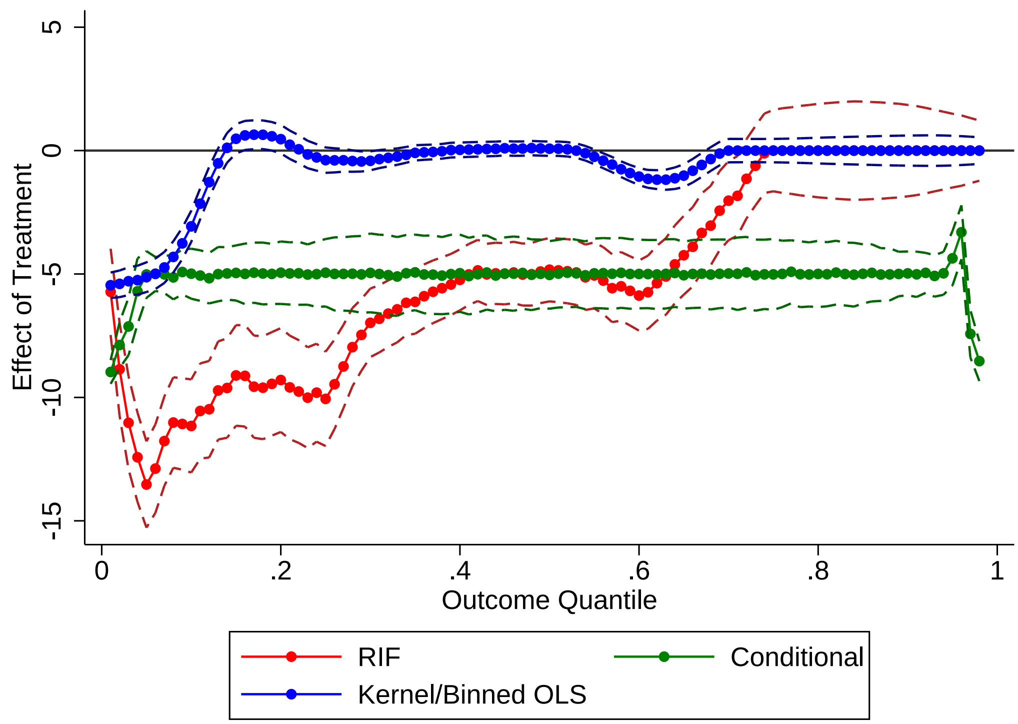
	Change All Firms			Change Domestic Firms Only		
	1-veh	2-veh	3-veh	1-veh	2-veh	3-veh
	I	II	III	IV	V	VI
ln(pop)	0.105	0.190***	0.063***	-0.002	0.113*	0.047***
	(0.198)	(0.054)	(0.007)	(0.208)	(0.045)	(0.006)
ln(fatalities)	-0.145	-0.167*	-0.050***	-0.008	-0.103	-0.040***
	(0.245)	(0.067)	(0.009)	(0.257)	(0.056)	(0.007)
ln(wt)	-0.923	-0.688***	-0.175***	-0.778	-0.454***	-0.130***
	(0.551)	(0.150)	(0.020)	(0.577)	(0.125)	(0.016)
ln(age)	0.311	0.911***	0.287***	-0.559	0.565**	0.210***
	(0.957)	(0.261)	(0.035)	(1.002)	(0.217)	(0.028)
LD Truck	0.210	-0.070	-0.033***	0.535**	-0.039	-0.023***
	(0.165)	(0.045)	(0.006)	(0.173)	(0.037)	(0.005)
US	-0.701	-0.778***	-0.220***	0.035	-0.503**	-0.160***
	(0.789)	(0.215)	(0.028)	(0.826)	(0.179)	(0.023)
Asian	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
ln(fatalities) x Asian	0.239	0.194**	0.055***	0.086	0.121	0.044***
	(0.273)	(0.074)	(0.010)	(0.286)	(0.062)	(0.008)
ln(fatalities) x US	0.110	0.162*	0.050***	-0.034	0.098	0.040***
	(0.246)	(0.067)	(0.009)	(0.258)	(0.056)	(0.007)
ln(pop) x Asian	-0.172	-0.217***	-0.070***	-0.045	-0.132**	-0.052***
	(0.220)	(0.060)	(0.008)	(0.231)	(0.050)	(0.006)
ln(pop) x US	-0.079	-0.184***	-0.063***	0.030	-0.109*	-0.047***
	(0.199)	(0.054)	(0.007)	(0.209)	(0.045)	(0.006)
Constant	7.258*	4.347***	1.022***	7.107*	2.926***	0.764***
	(3.238)	(0.883)	(0.117)	(3.392)	(0.735)	(0.094)
R-squared	0.33	0.38	0.62	0.41	0.30	0.62
N	357	357	357	357	357	357

Notes: Standard errors are given in parentheses with * indicating significance at 5%, ** at 1%, and *** at >1%.

Table A22: SDS State to National Imputation



(a) Monte Carlo Data



(b) Recovered Estimates from Three Approaches

Figure A1: Example of Technique