Carbon Prices and Automobile Greenhouse Gas Emissions: The Extensive and Intensive Margins

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Abstract

The transportation sector accounts for nearly one third of the United States greenhouse gas emissions. Despite this, US policy to reduce greenhouse gas emissions from vehicles has been essentially stagnant since 1990. Policy makers have avoided directly pricing externalities from vehicles, in terms of both global and local pollutants, and Corporate Average Fuel Standards have changed little since the mid-1980s. As well, the emission reductions from policies designed to increase bio-fuel penetration have been called into question. This paper analyzes how pricing carbon through either a cap and trade system or carbon tax might affect greenhouse gas emissions from the transportation sector. We analyze their effect on both the intensive (e.g., vehicle miles travelled) and extensive (e.g., vehicle scrapping) margins. We find large effects on both margins.

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1 Introduction

The transportation sector accounts for nearly one third of the United States greenhouse gas emissions. Despite this, US policy to reduce greenhouse gas emissions from vehicles has been essentially stagnant since 1990. Policy makers have avoided directly pricing the externalities from vehicles, both in terms of global and more local pollutants, and Corporate Average Fuel Standards have changed little since the mid-1980s. Finally, the emission reductions from policies designed to increase bio-fuel penetration have been called into question.

This paper analyzes how pricing carbon through either a cap and trade system or carbon tax might affect greenhouse gas emissions from the transportation sector. Pricing carbon can influence emissions from the transportation sector in a number of ways. On the firm side, a positive carbon price incentivizes firms to reduce lifecycle emissions from liquid fuels either through the refining process or by switching to fuels that have a lower carbon content. Pricing carbon also incentivizes automobile manufacturers to change their product mix. On the consumer side, pricing carbon differentiates fuels by their carbon content, so consumers have an incentive to switch to cleaner gasoline or alternative fuels. Consumers also have an incentive to drive more efficiently and to keep their vehicles operating more efficiently. The scrapping decisions of consumers are also affected. High mileage vehicles may stay on the roader longer as they become relatively more valuable, while low mileage vehicles may exit faster. New vehicle decisions are also likely to change as consumers switch to more fuel efficient vehicles. Finally, driving habits and trip decisions may also be affected, reducing the number of miles driven.

We focus on these last three factors: scrappage decisions, new vehicle demand, and vehicle miles travelled. We find statistically and economically significant effects on all three dimensions.

We bring together a number of unique data sets. The first is the universe of test records California's emissions inspection and maintenance program for the period of 1996 to 2009. California requires vehicles older than six years to receive biennial testing. In addition, testing occurs each time a vehicle changes ownership and randomly for a small share of vehicles. Among other things, the inspection data report odometer readings, which we use to measure vehicle miles travelled between tests. To measure greenhouse gas emissions, we link these data to EPA fuel economy ratings. In addition, the data are linked to EIA gas prices for the same years.

Our work builds on a recent literature analyzing how changes in gasoline prices influence consumer behavior. On the extensive margin, Busse, Knittel, and Zettelmeyer (2009) study purchase decisions and dealer pricing decisions using transaction-level data for both new and used vehicles. They find that increased gasoline prices influence both which vehicles consumers buy and the prices they pay for them in both the new and used vehicle markets. Furthermore, market shares are most influenced in the new vehicle market, while prices are most affected in the used market. Using model-level registration data for twenty MSAs, Li, Timmins, and von Haefen (2009) finds higher gas prices affect both new vehicle purchase decisions and used vehicle scrapping decisions. Hughes, Knittel, and Sperling (2008) estimate the short run elasticity for gasoline and find that over time elasticities have fallen.

Most of these papers use monthly variation in gasoline prices for their empirical results. Therefore, their results are short run in nature. One of the contributions of this paper is that because of the richness of our data, in particular a large number of individual decisions that take place throughout the year, we are able to estimate how changes in gas prices affect decisions that take place within two-year intervals. For example, one of our empirical exercises asks how a change in the price of gasoline over a two year period affects vehicle miles travelled. While we make use of monthly variation in gasoline prices, we are able to take this more long run approach because we observe a large number of different two-year intervals. To estimate a "two-year elasticity" with aggregate data would require a much longer time series than researchers typically possess.

The paper proceeds as follows. Section 2 discusses the empirical setting. The data are discussed in Section 3. Section 4 provides graphical support for the two channels, while Section 5 presents the empirical models and results. Finally, Section 6 concludes the paper.

2 Empirical Setting

Our empirical setting is California. Our primary data source is the universe of test data from California's Smog Check program from 1996 to 2009. California implemented its first inspection and maintenance program in 1984 in response to the 1977 Clean Air Act amendments. The initial incarnation of the Smog Check program relied purely on a decentralized system of privately run, state-licensed inspection stations, and was plagued by cheating and lax inspections. Although the agreement between California and the federal EPA promised reductions in hydrocarbon and carbon monoxide emissions of more the 25 percent, estimates of actual reductions of the early Smog Check Program range from zero to half that amount (Glazer, Klein, and Lave (1995)).

The 1990 Clean Air Act amendments required states to implement an enhanced inspection and maintenance program in areas with serious to extreme non-attainment of ozone limits. Several of California's urban areas fell into this category, and in 1994, a redesigned inspection program was passed by California's legislature after reaching a compromise with the EPA. The program was updated in 1997 to address consumer complaints, and fully implemented by 1998. Among other improvements, California's new program introduced a system of centralized "Test-Only" stations and an electronic transmission system for inspection reports.[1] Today, more than a million Smog Checks take place each month.

An automobile appears in our data for a number of reasons. First, vehicles that are older than four years old must pass a smog test within 90 days of any change in ownership. Second, in parts of the state (details below) an emissions inspection is required every other year concurrent as a pre-requisite for renewing the registration on the vehicle for vehicles that are seven years or older. Third, a test is required if a vehicle moves from out-of-state. Finally, some vehicles are flagged as matching a High Emitter Profile (HEP) and must receive a Smog Check every year before registering. Vehicles which fail an inspection must be repaired and receive another inspection before they can be registered and driven in the state. There is also a group of exempt vehicles. These are: vehicles of 1975 model-year or older, hybrid and electric vehicles, motorcycles, diesel powered vehicles, and large trucks powered by natural gas.

Since 1998, the state has been divided into three inspection regimes (recently expanded to four), the boundaries of which roughly correspond to the jurisdiction of the Regional Air Quality Management Districts. "Enhanced" regions, designated because they fail to meet state or federal standards for carbon monoxide (CO) and ozone, fall under the most restrictive regime. All of the state's major urban centers are in Enhanced areas, including the greater Los Angeles, San Francisco, and San Diego metropolitan areas. Vehicles registered to an address in an Enhanced area must pass a biennial Smog Check in order to be registered, and they must take the more rigorous Acceleration Simulation Mode (ASM) test, which involves the use of a dynamometer. In addition, a randomly selected two percent sample of all vehicles in these areas is directed to have their Smog Checks at so-called Test-Only stations, which are not allowed to make repairs[2]. HEP vehicles are also directed to Test-Only stations, as are vehicles which are flagged as "gross polluters"

[1] For more detailed background see http://www.arb.ca.gov/msprog/smogcheck/july00/if.pdf.

[2] Other vehicles can be taken to Test-Only stations as well if the owner chooses, although they must get repairs elsewhere if they fail

(this occurs when a vehicle fails an inspection with twice the legal limit of one or more pollutant in its emissions). More recently some "Partial-Enhanced" areas have been added, where a biennial ASM test is required, but no vehicles are directed to Test-Only stations.

Areas with poor air quality that does not exceed legal limits fall under the Basic regime. Cars in a Basic area must have biennial Smog Checks as part of registration, but they are allowed to take the more lax Two Speed Idle (TSI) test, and no vehicles are directed to Test-Only stations. The least restrictive regime, consisting of rural mountain and desert counties in the east and north of the state, is known as the Change of Ownership area. As the name suggests, inspections in these areas are only required upon change of ownership; no biennial Smog Check is required.

3 Data

Our data come from the Bureau of Automotive Repair (BAR) and are the universe of Smog Check test records from 1996 to 2010 and report the location of the test, the vehicle's VIN, odometer reading, the reason for the test, and test results. We decode the VIN to obtain the vehicles' make, model, engine and transmission. Using this, we match the vehicles to EPA data on fuel economy. Because the VIN decoding only holds for vehicles made after 1981, our data are restricted to these models, although to date we have only matched the EPA data for model years 1984 to the present. We also restrict our sample to 1998 and beyond given the large changes that occurred in 1997. This yields roughly 120 million observations. For the analysis in this paper we use a random 10 percent sample.

For biennial tests, we construct the average gasoline price between the two test data using EIA's national average prices.

4 Initial Evidence

Before discussing the econometric models and results, we provide evidence that increasing fuel prices affects both the intensive and extensive margins.

4.1 Extensive Margin

Changes in the extensive margin will manifest themselves in changing the mix of vehicles that are registered through both scrappage and new vehicle sales. We present evidence of both. Figure 1 plots both gas prices and the average fuel economy of newly registered vehicles within one year of the current year. While the Smog Test program does not require dealers to test new vehicles, tested vehicles within one year of the current year are likely to correlate well with new vehicle sales.[3]

From 1998 to 2004, there was a steady decrease in the fuel economy of new vehicles registered in California. This corresponds to the increase in SUV sales and a period of relatively low gasoline prices. As gasoline prices rose, however, this trend reversed. The trend again reverses as gasoline prices began to fall in 2008. We take this as evidence, consistent with Busse, Knittel, and Zettelmeyer (2009) that new vehicle sales respond to gasoline prices. Indeed, this figure extends their analysis to include the drop in gasoline prices beginning in 2008.

As evidence that scrappage rates respond to gasoline prices, we plot the average fuel economy of vehicles of a specific model year over time. If the scrappage rates of vehicles of a specific vintage are independent of a vehicle's fuel economy or gasoline prices, then the average fuel economy of a particular model-year over time will be constant. There is reason to believe, however, that less fuel efficient vehicles have lower hazard rates since trucks typically last longer than passenger cars.[4]

Figure 2 plots the average fuel economy of vehicles with model years of 1984, 1986, 1988, and 1990 being tested as part of either the random or biennial test programs, as well as gasoline prices. The model years are old enough to be at risk of scrappage and required biennial Smog Checks in each year of our data. All four model years, early in the sample, show a general decreasing trend in fuel economy, consistent with the higher durability of low fuel economy vehicles. This trend continues even as gasoline prices begin to rise in 2003. However, this trend appears to break–and in three of the four cases reverse–as gasoline prices rise further. Finally, we note that the trends appear to break at a similar point in calendar time despite the fact that these model years span 6 years. This suggests that the break in trend is not a vintage effect.

[3]The graphs in this section smooth the series using a lowess smoothed line with a bandwidth equal to four months.

[4]Therefore, all else equal, we might expect the average fuel economy of a given model year to fall over time. See, for example, Lu (2006) which finds different scrappage rates for cars and trucks.

4.2 Intensive Margin

We present preliminary evidence that gasoline prices affect the intensive margin by plotting monthly gas prices and the average miles driven (VMT) daily within a year (Figure 3). The figure suggests that VMT rose from 1998 to 1999 and then began a steady decline. This corresponds to the period where gasoline prices began to rise. We also see a small increase in VMT during 2009, which corresponds to the decrease in gasoline prices, albeit with some lag. Figure 4 plots the distribution of VTM in 1998 and 2008. The figure suggests a shift in the entire distribution over this time period.

5 Empirical Models and Results

5.1 Extensive Margin

Our first empirical model estimates the hazard rate of the decision to scrap a vehicle as a function of the cost per mile of the vehicle. We approximate a Cox proportional hazard model by estimating linear probability models with year fixed effects. Our empirical specifications vary the set of additional fixed effects.[5] They all include a sixth-order polynomial in the vehicle's odometer. We restrict our sample to those vehicles that are likely "at risk" of being scrapped, defined as vehicles ten years or older. The results are robust to moving this cutoff around. The key covariate is a vehicle's cost per mile during the period after a biennial smog test. We calculate the average gasoline price for the two years after the vehicle took the test and divide this by its fuel economy rating.[6]

We define a vehicle as being scrapped if it had a biennial smog test in year X, but does not have another smog test by year $X + 3$. We face two issues with this definition. First, the vehicle may have simply moved from a county requiring biennial tests to one that did not. Second, the vehicle may have moved out of state. We can partly deal with the first issue by also looking to see if the vehicle was tested because of change of ownership. If this occurs, we classify the vehicle as not scrapped. We argue that this will tend to bias our coefficients towards zero. If a subset of the vehicles move out of the testing area, and we classify this as being scrapped and these decisions are

[5]For the empirical models without make/model/engine/model year fixed effects we have estimated logit models yielding similar results. We have been unable to get the logit models to converge when including the more extensive set of fixed effects discussed below.

[6]Future work will use the actual two test dates and calculate the average gasoline price between these test dates, since they may not correspond to exactly two years. The calculations required for this were too time consuming for this version.

less influenced by gasoline prices than scrappage decisions, then our coefficient will underestimate the true impact of gasoline prices on scrapping rates.

As gasoline prices increase, the cost of operating all vehicles increase. All else equal, this will tend to increase the hazard rate for all vehicles. However, there is also a more general equilibrium effect. Busse, Knittel, and Zettelmeyer (2009) find that prices for fuel efficient vehicles increase as gasoline prices increases. This implies that as gasoline prices increase the "continuation value" of fuel efficient vehicles might also increase, despite their increase in usage costs. This may reduce the scrapping rates of these vehicles. For this reason, we separate the effect of change in cost per mile by fuel efficiency quartile.

Table 2 reports the results. Model 1 includes the dollars per mile of the vehicle as the key regressor along with a dummy for whether the vehicle is a truck, the polynomial in the odometer reading, year fixed effects, vintage fixed effects, and make fixed effects. Model 2 splits the effect of dollars per mile by whether the vehicle falls in the first, second, third, or fourth fuel economy quartile.[7] Curiously both Models 1 and 2 suggest that increases in the per mile cost of driving reduces the chances a vehicle is scrapped. We believe this result is driven by not adequately controlling for vehicle characteristics. Low fuel efficient vehicles are often more durable than their higher fuel efficient counterparts. The negative correlation between the cost per mile and scrapping decision may be capturing this. This is confirmed if we look at the average hazard rate by fuel efficiency quartile. Among vehicles that are older than 9 years old, the average hazard rate of the lowest quartile vehicles is 19 percent; it is 24, 25 and 28 percent for the second, third, and fourth quartiles, respectively.

To account for this, Models 3 through 6 include make/model/engine/model-year fixed effects. Once this richer set of fixed effects is included, we find that increases in cost per mile increase the hazard rate of vehicles (Model 3). Furthermore, when we allow cost per mile to have a different effect depending on the fuel efficiency quartile of the vehicle, we find that the hazard rate of the bottom quartile vehicles increases, while the hazard rate of high fuel efficiency vehicles falls (Models 4 through 6). The middle two quartiles are largely unaffected.

To put the estimates from Model 4 into perspective, the average fuel efficiency of a bottom quartile vehicle is 16.7 MPG. A one dollar increase in gasoline prices increases the cost per mile of these vehicles by roughly 6 cents, increasing the hazard by 5.7 percentage points. Given that the

[7] We define the quartiles across the entire sample, but the results are robust to defining them within year as well.

average hazard rate is 19 percent, this represents a 30 percent increase in the hazard. The average fuel efficiency of a fourth quartile vehicle is 30.3 MPG, implying a one dollar increase in gas prices, increases the cost per mile of these vehicles by 3.3 cents, decreasing the hazard of scrappage by 3.5 percentage points. At an average hazard of 28 percent, this is a 12.5 percent *decrease* in the hazard rate.

Models 5 and 6 split the at-risk vehicles into those between 10 and 14 years old and those 15 years and older. As we would expect, the effect on older vehicles is more pronounced. For bottom quartile vehicles that are between 10 and 14 years old, a one dollar increase in gas prices increases the hazard rate by 13 percent, but increases the hazard by 28 percent for vehicles older than 14 years old.[8] A one dollar increase in gasoline prices reduces the hazard of fuel efficient vehicles that are between 10 and 15 years old by 9 percent, but decreases the hazard by 28 percent for those vehicles older than 14 years old.

We next turn to the effect of gasoline prices on new car purchases. Admittedly, our data are not ideal for this since "cars off the lot" are not required to be tested, so we only capture relatively new vehicles that move into California. We regress the fuel economy of new vehicles on gasoline prices, defining fuel efficiency as miles per gallon or gallons per mile.[9] We vary the functional form assumptions and include fixed year and month of year effects. Table 3 reports the results. The first column reports the results with both fuel economy and gasoline prices measured in levels. The results suggest a one dollar increase in gasoline prices increase new vehicle fuel economy by roughly 0.3 MPG. This is much smaller compared to those results in Busse, Knittel, and Zettelmeyer (2009) which finds results on the order of one MPG per one dollar change in gasoline prices. The second model includes the log of gasoline prices as the regressor and finds a 10 percent increase in gasoline prices increases new vehicle fuel efficiency by 5.6 percent.

The last three models define the dependent variable in terms of gallons per mile. Column three suggests that a one dollar increase in gasoline prices reduces gallons per mile by 6×10^{-4}. At the average fuel economy of new vehicles in the data, this represents a 1.2 percent decrease. The final column defines fuel efficiency in terms of the log of gallons per mile and gasoline prices in logs, thus estimating an elasticity.[10] We estimate an elasticity of roughly 2.6. Again, this is smaller than those found in Busse, Knittel, and Zettelmeyer (2009).

[8]These calculations use the vintage-specific unconditional hazard for the denominator.

[9]For issues such as climate change gallons per mile is the more relevant metric.

[10]This is equivalent to defining the dependent variable as the log of miles per gallon.

5.2 Intensive Margin

We next estimate how gasoline prices affect the intensive margin. To do this, we calculate the change in the odometer reading between biennial tests for each vehicle and the average gasoline prices during the two years between tests.[11] This leaves roughly 1.8 million observations in our 10 percent sample.

As with the hazard model, we vary the set of fixed effects included. The key independent variable is either the log of gasoline prices (Table 4) or the of log dollars per mile (Table 5). Model 1 in Table 4 includes just year fixed effects, vintage fixed effects and a truck indicator variable. The results suggest a VMT elasticity of 0.442. It is important to note that while we are using within year variation in gasoline prices, because we are estimating the effect of a 1 percent change in gasoline prices over the entire two-year period, these estimates represent fairly long run elasticity. We believe that this makes these results unique in the sense that the individual level data allow us to estimate long run elasticities without aggregating the time series of the data (e.g., this would be infeasible using average monthly or yearly California VMT over a two-year period). Because of this, these estimates are larger than recent estimates of short run elasticities (e.g., Hughes, Knittel, and Sperling (2008)). Model 2 adds manufacturer fixed effects to Model 1. The results change very slightly. Model 3 allows the elasticity to vary by fuel efficiency quartile and finds very similar results across quartiles.

Models 4 and 5 include make/model/engine/model year fixed effects. The average elasticities changes very little, but a significant amount of heterogeneity exists. The top quartile vehicles' elasticity is less than half that of bottom quartile vehicles. One potential explanation for this is that we observe within household substitution from the fuel inefficient vehicles to the fuel efficient vehicles. We are exploring this in current work.[12] Another potential explanation is that a given change in gasoline prices implies a larger change in the cost per mile for fuel inefficient vehicles. But, we note that the rich fixed effects in Models 4 and 5 imply that we are looking *within* vehicle type. Indeed, Table 5 suggests that when we do not account for the vehicle type (Models 2 through 3) the results with the log of gasoline prices and the log of cost per mile differ considerably.[13]

[11] In principle we could use all tests, but the loop to calculate the average gasoline price between each of these tests was too slow for this version.

[12] This is consistent with the household bargaining that took place for one of the authors.

[13] Because they include both time and vehicle-type fixed effects, Models 4 and 5 are identical across the two specifications.

6 Conclusions

This paper estimates how changes in gasoline prices effect both the extensive and intensive margins of automobile use. We find significant effects on scrapping decisions, new vehicle purchase decisions, and miles travelled. The results highlight the variety of avenues in which carbon pricing policies may affect emissions from the transportation sector.

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Appendix

1 Figures

Figure 1: Average Fuel Economy of New Vehicles Registered in California

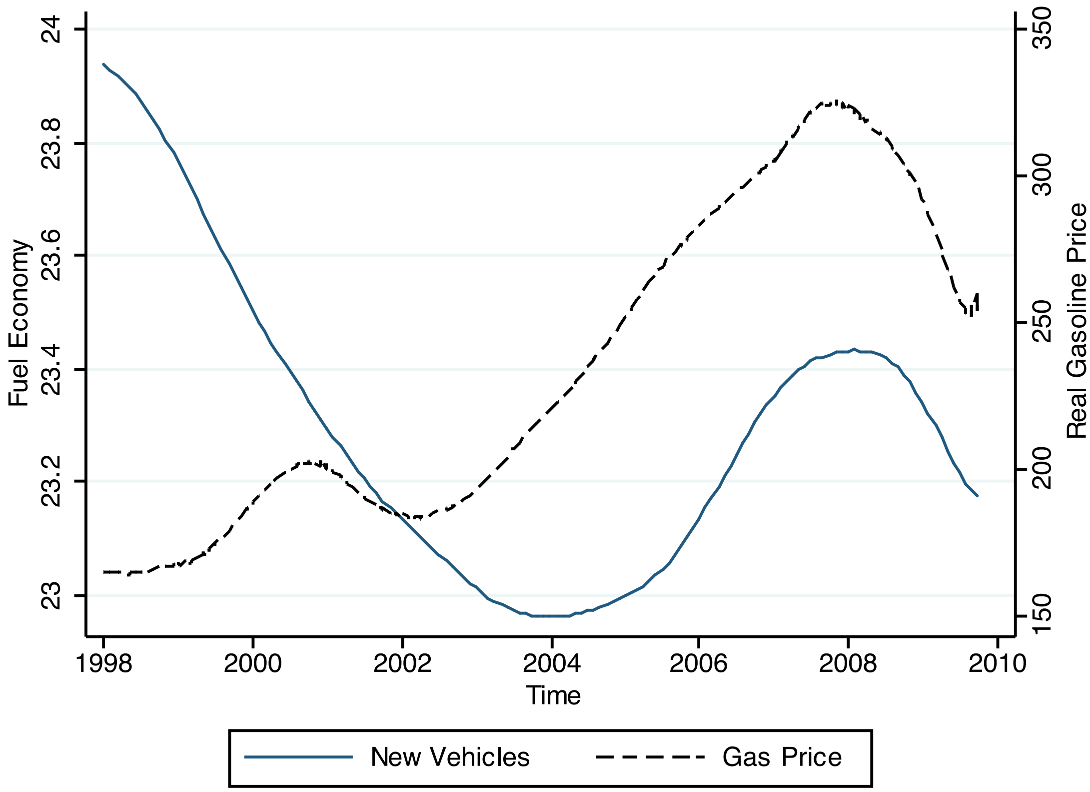


Figure 2: Average Fuel Economy for Vehicles with Model Years of 1984, 1986, 1988, and 1990 over Time

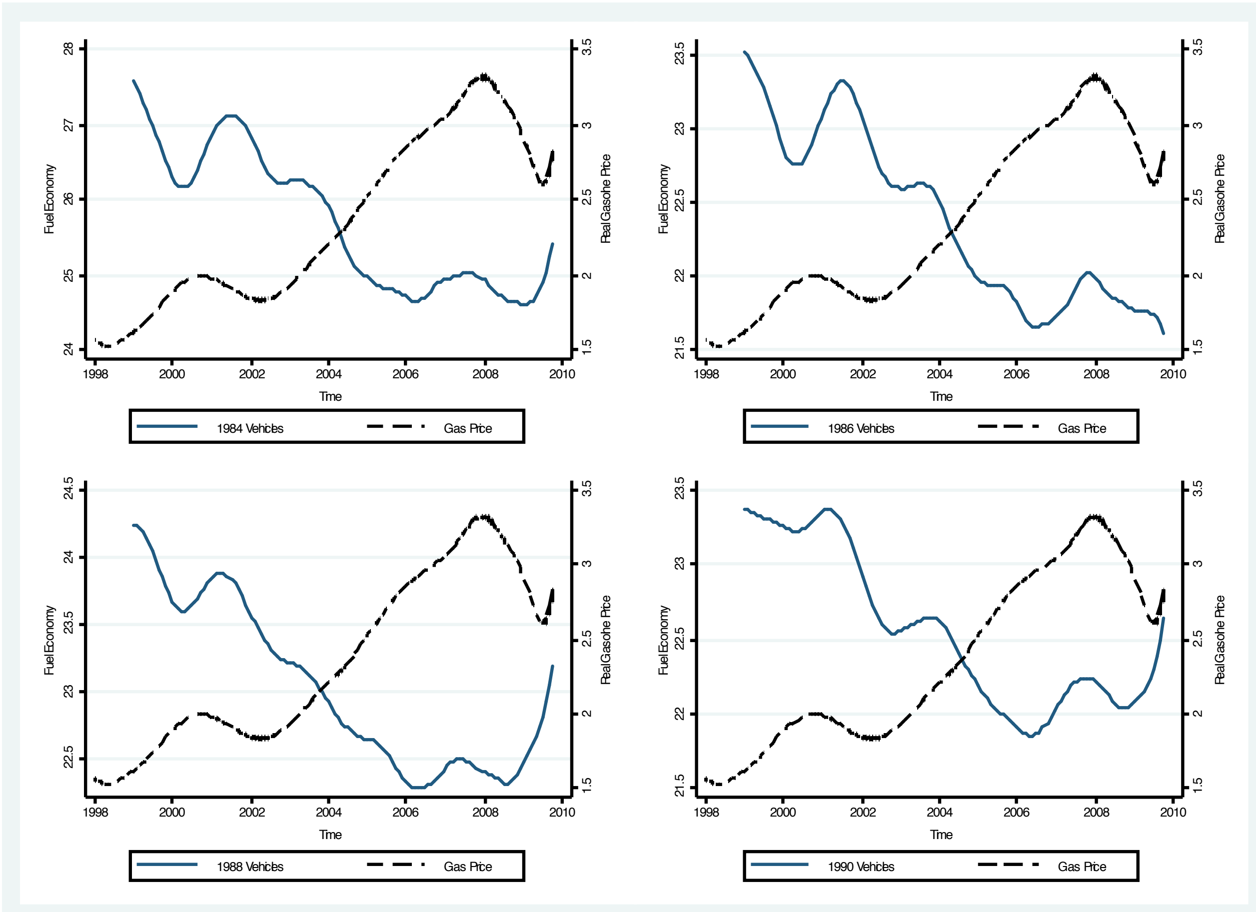


Figure 3: Average Miles Driven per Day and Gasoline Prices

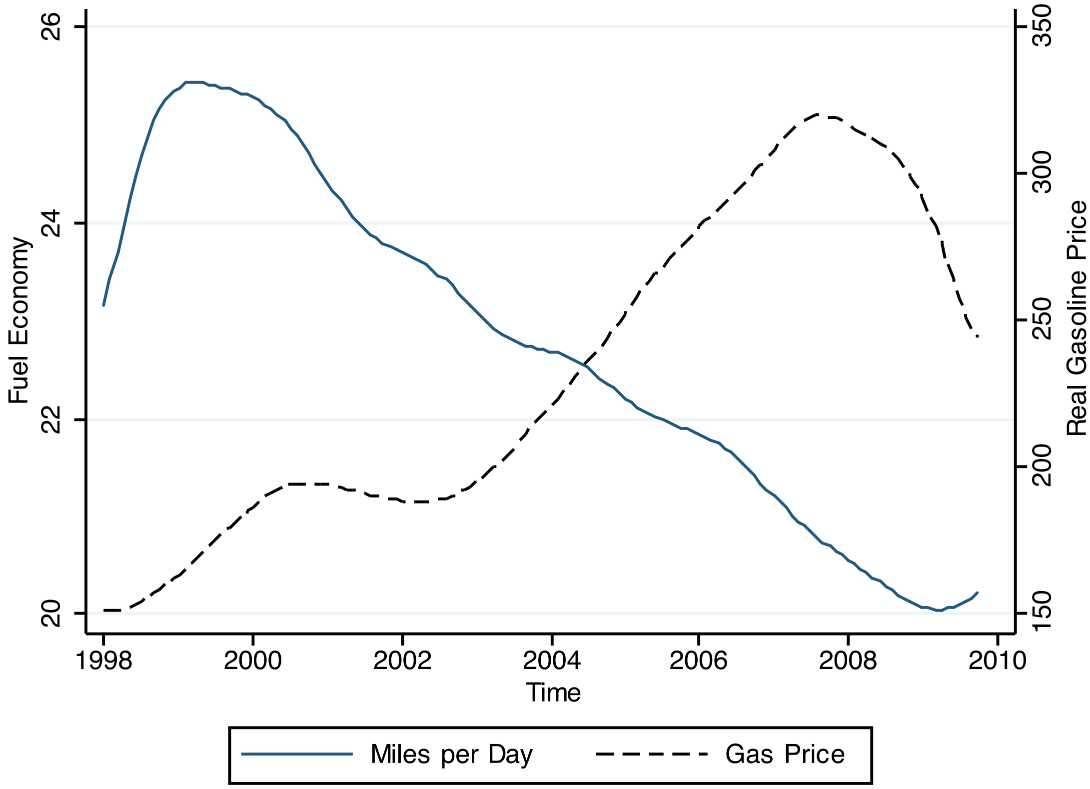
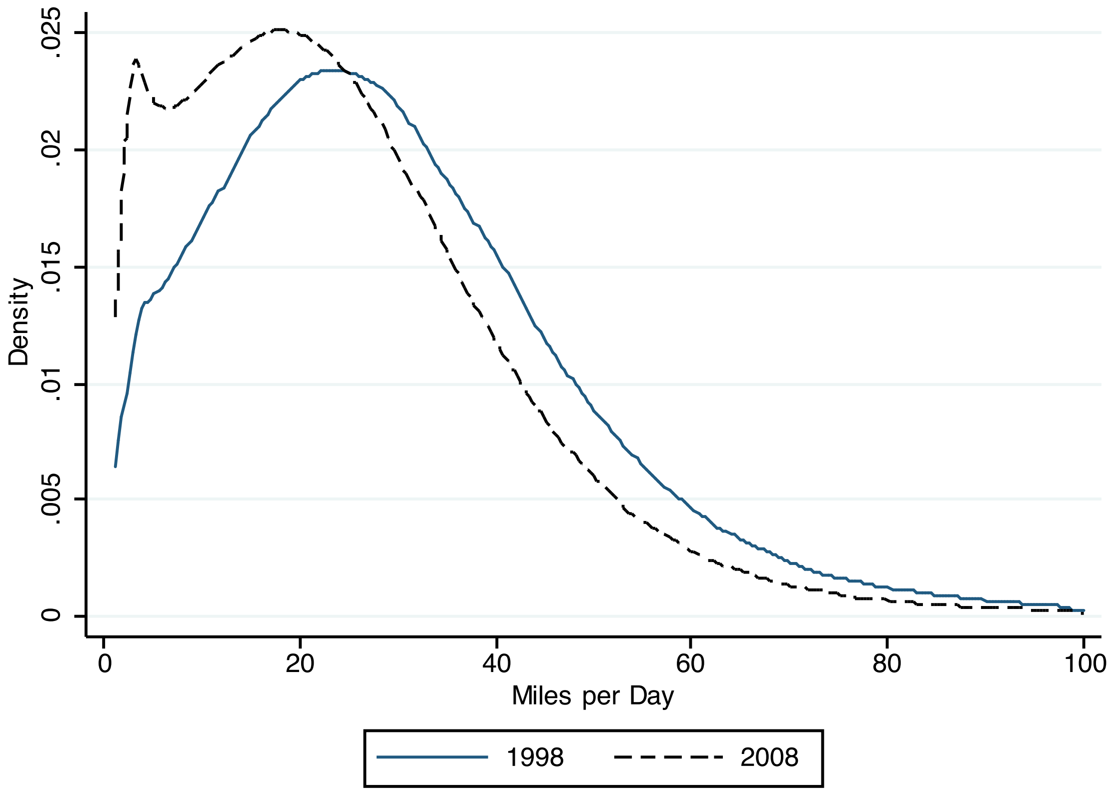


Figure 4: Distribution of Miles Driven per Day in 1998 and 2008



2 Tables

Year	Count	MPG	VMT/day	Gasoline Price	Cents/Mile
1998	661,729	23.92	33.42	1.52	7.31
1999	512,168	23.98	34.62	1.75	7.74
2000	869,975	23.78	30.84	2.09	8.45
2001	791,347	23.77	31.95	1.95	8.48
2002	788,716	23.56	29.40	1.82	8.49
2003	809,615	23.45	30.30	2.04	9.30
2004	1119371	23.29	28.07	2.38	10.59
2005	833,477	23.30	28.88	2.71	12.02
2006	953,961	23.17	27.23	3.02	13.33
2007	877,855	23.16	27.32	3.10	14.27
2008	959,873	23.05	25.84	3.71	14.73
2009	799,774	23.06	26.27	2.45	14.37

Table 1: Means of Greenhouse Gas Emission-related Variables

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dollars per Mile	-1.133**		1.584**			
	(0.054)		(0.242)			
Dollars per Mile * MPG Quartile 1		-0.791**		0.951**	0.481	1.173*
		(0.089)		(0.274)	(0.341)	(0.533)
Dollars per Mile * MPG Quartile 2		-1.667**		-0.066	0.228	-1.219+
		(0.147)		(0.355)	(0.424)	(0.711)
Dollars per Mile * MPG Quartile 3		-2.138**		-0.049	0.056	-1.243
		(0.178)		(0.417)	(0.496)	(0.861)
Dollars per Mile * MPG Quartile 4		-2.358**		-1.061*	-1.001	-2.436*
		(0.180)		(0.506)	(0.621)	(1.006)
Truck	-0.007**	-0.001				
	(0.002)	(0.003)				
Odometer	-0.216**	-0.218**	-0.203**	-0.205**	-0.181**	-0.316**
	(0.020)	(0.020)	(0.020)	(0.020)	(0.022)	(0.049)
Odometer2	0.248**	0.249**	0.252**	0.253**	0.233**	0.356**
	(0.020)	(0.020)	(0.020)	(0.020)	(0.022)	(0.050)
Odometer3	-0.098**	-0.099**	-0.102**	-0.103**	-0.097**	-0.145**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.023)
Odometer4	0.018**	0.018**	0.019**	0.019**	0.018**	0.027**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)
Odometer5	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Odometer6	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MPG Quartile 1		-0.135**				
		(0.013)				
MPG Quartile 2		-0.047**				
		(0.013)				
MPG Quartile 3		-0.002				
		(0.014)				
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Vintage Fixed Effects	Yes	Yes	--	--	--	--
Make Fixed Effects	Yes	Yes	--	--	--	--
Make*Model*Engine*Model Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Sample	Vintage>9 Yrs	Vintage>9 Yrs	Vintage>9 Yrs	Vintage>9 Yrs	9<Vintage<16	Vintage>15 Yrs
Observations	293753	293753	293175	293175	256014	37161
R-squared	0.186	0.186	0.274	0.276	0.268	0.314

Standard errors in parentheses. Clustered at the Make/Model/Engine/Model Year level.
+ denotes significance at the 0.10 level, * at the 0.05 level, and ** at the 0.01 level.

Table 2: Probability of Exit as a Function of Gasoline Prices – Linear Probability Model

	MPG	**MPG**	**GPM**	**GPM**	**ln(GPM)**
Gasoline Price	0.287**		-0.001**		
	(0.061)		(0.000)		
ln (Gasoline Price)		0.563**		-0.001**	-0.026**
		(0.153)		(0.000)	(0.007)
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	202480	202480	202480	202480	202480
R-squared	0.010	0.010	0.009	0.009	0.009

Table 3: "New" Vehicle Fuel Economy and Gasoline Prices

	Model 1	Model 2	Model 3	Model 4	Model 5
ln of Gasoline Price	-0.442**	-0.459**		-0.440**	
	(0.018)	(0.018)		(0.018)	
ln of Gasoline Price * MPG Quartile 1			-0.458**		-0.625**
			(0.018)		(0.022)
ln of Gasoline Price * MPG Quartile 2			-0.460**		-0.444**
			(0.018)		(0.022)
ln of Gasoline Price * MPG Quartile 3			-0.458**		-0.351**
			(0.018)		(0.023)
ln of Gasoline Price * MPG Quartile 4			-0.454**		-0.288**
			(0.018)		(0.022)
Truck	0.091**	0.112**	0.124**		
	(0.001)	(0.001)	(0.002)		
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Vintage Fixed Effects	Yes	Yes	Yes	Yes	Yes
Make Fixed Effects	No	Yes	Yes	--	--
Make*Model*Engine*Model Year Fixed Effects	No	No	No	Yes	Yes
Observations	1752238	1752238	1752238	1752238	1752238
R-squared	0.076	0.097	0.097	0.150	0.151

Table 4: Vehicle Miles Travelled and Gasoline Prices

	Model 1	Model 2	Model 3	Model 4	Model 5
ln of Gasoline Price	-0.292**	-0.096**		-0.440**	
	(0.014)	(0.012)		(0.020)	
Dollars per Mile * MPG Quartile 1			-0.140**		-0.625**
			(0.016)		(0.022)
Dollars per Mile * MPG Quartile 2			-0.156**		-0.444**
			(0.017)		(0.022)
Dollars per Mile * MPG Quartile 3			-0.156**		-0.351**
			(0.018)		(0.023)
Dollars per Mile * MPG Quartile 4			-0.158**		-0.288**
			(0.019)		(0.022)
Truck	0.179**	0.141**	0.135**		
	(0.007)	(0.006)	(0.006)		
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Vintage Fixed Effects	Yes	Yes	Yes	Yes	Yes
Make Fixed Effects	No	Yes	Yes	--	--
Make*Model*Engine*Model Year Fixed Effects	No	No	No	Yes	Yes
Observations	1752238	1752238	1752238	1752238	1752238
R-squared	0.079	0.097	0.097	0.150	0.151

Table 5: Vehicle Miles Travelled and Dollars per Mile