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Advanced and Alternative Fuel Vehicle Policies: Regulations and Incentives in the United States

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Abstract

Transportation policy is playing an increasingly important role in the transition towards more fuel-efficient vehicles and alternative fuel vehicles (AFVs). Whether the policy seeks to promote adoption through mandatory requirements or through monetary incentives, or to address issues related to adoption of AFVs, it is clear that such policies can have large-ranging impacts on the future of the US transportation system. The work I conduct in my dissertation seeks to understand these policies, in the past, present, and future.

I evaluate the effects of the Energy Policy Act of 2005 (EPACT) on the adoption of HEVs. As part of EPACT, a tax credit incentives program was implemented for consumers purchasing HEVs. Using a unique fixed effects regression approach with lagged instrumental variables, I am able to estimate the effects of the incentives. I find the most significant responses occur when incentives exceed $1,000 in tax credit. Depending on the vehicle model the presence of EPACT yielded increases in sales of 5% to 15%. This increase is relatively smaller compared to many existing studies, which my work indicates is likely the result of over-attribution of sales to policy.

I go on to examine the effects of the adoption of electric vehicles on funding for transportation infrastructure. A significant portion of revenue for transportation infrastructure comes from taxes on gasoline, these funds will likely be diminished to some extent as electric vehicles are adopted as they consume little to no gasoline as fuel. Using several existing electric vehicle models, I find that at the per-vehicle level, revenue generation can be upwards of 50% lower in certain states depending on how fees are charged. The total annual revenue generation at the federal level could decrease by as much as $200 million by 2025, though this is quite a small portion of total revenues for transportation infrastructure. I demonstrate that the revenue decrease can easily be made up through small policy fee changes in either flat fixed or through incremental increases in use fees, though implementation of such policies can be difficult politically.

I also focus on the recent implementation of alternative fuel vehicle incentives in the

2009 update of the CAFE standards. I demonstrate that while the AFV incentives help spur the production and adoption of AFVs, there is a short-term emissions penalty due to the structure of the policy. I find that every AFV sold results in an increase in emissions rate for another vehicle of 50-400 grams of CO_2 per mile, comparable to adding an additional conventional vehicle onto the road. The cumulative effect is an increase of 20 to 70 million metric tons of CO_2 for vehicles sold between 2012 and 2025. I further extends this work by investigating how other policies promoting AFV sales interact with the CAFE policy. I focus specifically on the California ZEV mandate interaction and find that there is an increase of 120 million metric tons of CO_2 for new cars sold between 2012 and 2025. The analysis also demonstrates a counterintuitive effect: the greater the success of ZEV in inducing adoption of AFVs, the greater the short-term emissions penalty due to the two policies.

Finally I examines the response of driving behavior response to changes in gasoline prices. Using a unique dataset obtained from Pennsylvanias Department of Transportation, we are able to observe annual driving behavior at the individual vehicle level from 2000 through 2010. We observe heterogeneity of price elasticities using two methods: separating data by quantiles over the factors of interest and by interacting the factors of interest as categorical variables with gasoline prices. We find statistically significant variations in elasticities: for driving intensities we observe values of -0.172 increasing up to -0.0576 as the amount driven annually increases, for gasoline prices we observe a range of elasticities from -0.002 to -0.05 for prices below $4/gallon with a sudden increase to -0.182 for prices above $4/gallon, lastly for fuel economies we find that below 20 MPG elasticities are highest at -0.173 with decreasing responsiveness as vehicle fuel economy increases. Heterogeneity needs to be accounted for in order to properly understand policy effects: responses based on average elasticity values are likely to be incorrect.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

Transportation is an integral component of the technological infrastructure in the United States. Beginning in the early 20th century, passenger vehicles have become a widespread product with over 300 million cars on the road in the US, approximately one vehicle for every man, woman, and child living in the country. Affordable personal transportation provides unprecedented mobility and redefines distance barriers in nearly all aspects of daily life. Commuting to school or work is practical at much longer distances, intra-city travel is both fast and convenient, and inter-city and even state-to-state travel is perfectly feasible using a car. However, the disadvantages and negative consequences of the energy use and emissions of our transportation system had arguably not been a topic of great importance amongst the public and policymakers in the US until the last two decades.

The size of the US transportation system is massive: in terms of energy consumption the transportation sector annually consumes almost one-third of all energy in the country. For comparison, consider the recent oil spill from the *Deepwater Horizon* rig in the Gulf of Mexico. Over the course of three months, approximately 200 million gallons of oil was spilled into the Gulf of Mexico. The personal transportation sector in the US consumes nearly twice as much oil as was spilled in this incident, 380 million gallons of gasoline, *every* day. The combustion of this oil releases approximately 2 billion metric tons of CO_2

equivalent into the atmosphere annually. Policymakers have recently recognized the large impact of transportation fossil fuel consumption and have made efforts to mitigate climate change by attempting to reduce carbon emissions from the transportation sector.

Oil consumption for transportation is also important from an energy security perspective. One of the earliest policies addressing concerns over oil security was the Corporate Average Fuel Economy (CAFE) standards, first passed in 1975 and regulated by the National Highway Traffic and Safety Administration. The regulation required manufacturers to attain a specific target for their sales-weighted fuel efficiency. However for a period of two decades from 1990 through 2010, CAFE standards stayed relatively constant and most vehicle manufacturers chose to improve other attributes of cars such as acceleration rather than improve fuel economy. Policy efforts to improve fuel efficiency and develop alternative fuel vehicles occurred at a regional level. One example is the 1990 Zero Emissions Vehicle (ZEV) regulation developed by the California Air Resources Board. While electric vehicles powered by lead batteries and hydrogen fuel cell vehicles failed to gain any traction in the 1990's, incremental technological improvements nevertheless reached the mass market. In 2000, the first hybrid electric vehicles (HEVs), the Toyota Prius and Honda Insight, became publicly available. Over the next decade, in conjunction with rising gasoline prices, the advent of hybrid vehicles has arguably led to an increased public awareness and valuation of fuel efficiency.

My dissertation seeks to understand the role of policies in the transition towards more fuel-efficient vehicles and alternative fuel vehicles. In Chapter 2, I evaluate the effects of the Energy Policy Act of 2005 (EPACT) on the adoption of HEVs. As part of EPACT, a tax credit incentives program was implemented for consumers purchasing HEVs. Using a unique fixed effects regression approach with lagged instrumental variables, I am able to estimate the effects of the incentives. I find the most significant responses occur when incentives exceed $1,000 in tax credit. Depending on the vehicle model the presence of EPACT yielded increases in sales of 5% to 15%. This increase is relatively smaller compared to many existing studies, which my work indicates is likely the result of over-attribution of sales to policy.

In Chapter 3, I evaluate the effects of the adoption of electric vehicles on funding for transportation infrastructure. A significant portion of revenue for transportation infrastructure comes from taxes on gasoline. These funds will likely be diminished to some extent as electric vehicles are adopted as they consume little to no gasoline as fuel. Using several existing electric vehicle models, I find that at the per-vehicle level, revenue generation can be upwards of 50% lower in certain states depending on how fees are charged. The total annual revenue generation at the federal level could decrease by as much as $200 million by 2025, though this is quite a small portion of total revenues for transportation infrastructure. I demonstrate that the revenue decrease can easily be made up through small fee changes in either flat fixed fees (such as annual registration fees) or through incremental increases in use fees, though the implementation of either policy change could be difficult politically.

Chapters 4 and 5 both focus on the recent implementation of alternative fuel vehicle (AFV) incentives in the 2009 update of the CAFE standards. In Chapter 4, I demonstrate that while the AFV incentives help spur the production and adoption of AFVs, there is a short-term emissions penalty due to the structure of the policy. I find that every AFV sold results in an increase in emissions rate for another vehicle of 50-400 grams of CO_2 per mile, comparable to adding an additional conventional vehicle onto the road. The cumulative effect is an increase of 20 to 70 million metric tons of CO_2 for vehicles sold between 2012 and 2025. Chapter 5 extends this work by investigating how other policies promoting AFV sales interact with the CAFE policy. I focus specifically on the California ZEV mandate interaction and find that there is an increase of 120 million metric tons of CO_2 for new cars sold between 2012 and 2025. The analysis also demonstrates a counterintuitive effect: the greater the success of ZEV in inducing adoption of AFVs, the greater the short-term emissions penalty due to the two policies.

Lastly, Chapter 6 examines the response of driving behavior response to changes in gasoline prices. Using a unique dataset obtained from Pennsylvanias Department of Transportation, we are able to observe annual driving behavior at the individual vehicle level from 2000 through 2010. We observe heterogeneity of price elasticities using two methods: separating data by quantiles over the factors of interest and by interacting the factors of interest as categorical variables with gasoline prices. We find statistically significant variations in elasticities: for driving intensities we observe values of -0.172 increasing up to -0.0576 as the amount driven annually increases, for gasoline prices we observe a range of elasticities from -0.002 to -0.05 for prices below $4/gallon with a sudden increase to -0.182 for prices above $4/gallon, lastly for fuel economies we find that below 20 MPG elasticities are highest at -0.173 with decreasing responsiveness as vehicle fuel economy increases. Heterogeneity needs to be accounted for in order to properly understand policy effects: responses based on average elasticity values are likely to be incorrect.

Chapter 2

The impact of federal incentives on the adoption of hybrid electric vehicles in the United States

2.1 Introduction

Efforts to promote the adoption of hybrid electric vehicles in the United States have been steadily increasing over the last decade in response to concerns over environmental impacts from fossil fuel combustion and to reduce consumption of foreign oil. Currently, hybrid electric vehicles (HEVs) represent the majority of available alternatives to traditional internal combustion engine (ICE) vehicles for personal transportation.

HEVs combine an internal combustion engine with an electric propulsion system that is powered by a large battery unit. The battery provides a higher fuel efficiency by using regenerative braking and preventing idling loses (by shutting off the engine), thus allowing most HEVs to at least raise their city-driving fuel efficiency to highway-driving fuel efficiency levels. The proposed benefits of higher fuel efficiency include less pollution and emissions as

Abbreviations: Hybrid Electric Vehicle (HEV), Internal Combustion Engine (ICE), Greenhouse Gas (GHG), Cash for Clunkers (C4C), Lagged Dependent Variable (LDV) well as gasoline savings without sacrificing the service provided, though typically at higher prices. These benefits are the primary reasons prompting the government to incentivize their use through tax credits and rebates. However, there is large uncertainty on whether these incentives have been able to induce adoption.

The Honda Insight and Toyota Prius were the first HEVs introduced in the market in the year 2000. Both models are offered only as HEVs. This was followed by the introduction of the Honda Civic Hybrid in 2002 as a hybrid variant of an originally ICE model. Since then, the number of make and models offering HEV alternatives has increased substantially. There are currently over 30 HEV models offered in the market. The majority are hybrid versions of ICE vehicles[1]. Figure 2.1 shows the number of available HEV models over time, from 1999 through 2010.

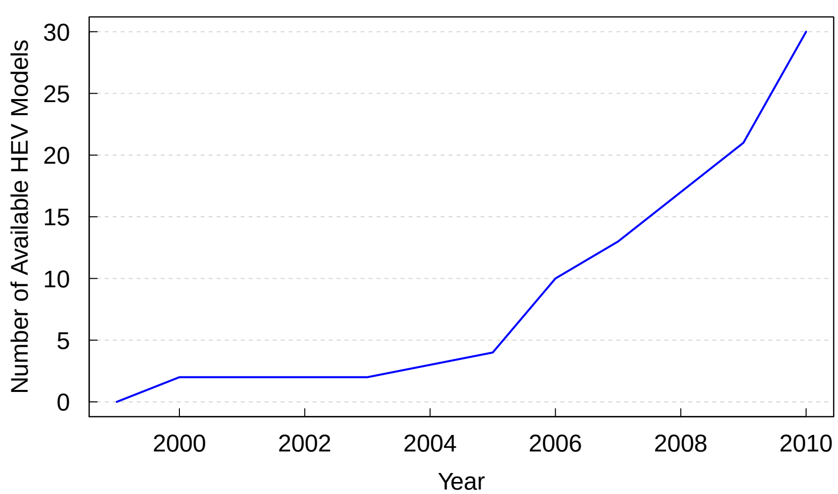


Figure 2.1: Number of HEV models commercially available over time[2]

Since the introduction of the Honda Insight and Toyota Prius in 2000, the government used several mechanisms to promote the adoption of HEVs. These mechanisms included a variety of incentives, both non-monetary and monetary. The first federal incentive was

[1] www.hybridcars.com: Hybrid Market Dashboard

[2] Compiled from AutoNews data archives at www.autonews.com

HR 1308, Section 319 of the Working Families Tax Relief Act of 2004 (Law No: 108-311) (Thomas, 2003). This Act established that the Internal Revenue Service (IRS) would provide a $2,000 taxable income deduction to an alternative fuel vehicle purchase. This included HEVs. The incentive applied for two years starting on January 1, 2004 with an upper bound expense of approximately $400 million to the US government[3]. In 2005 the Energy Policy Act in 2005 (Law No: 109-58) (Barton, 2005) , established a new set of incentives via a direct tax credit to consumers for the purchase of an HEV. This incentive was partially scaled to the fuel economy rating of the vehicle, so a greater efficiency would typically result in a higher incentive. In addition, a "phasing out" period was applied to the incentives: if any manufacturer sold 60,000 HEVs within one quarter, the incentives applied to their vehicles would halve twice over the course of the year before being phased out completely. This act was specifically aimed at reducing benefits for foreign vehicle manufacturing companies who had a larger command of alternative fuel vehicles at the time[4]. The Energy Policy Act of 2005 was successful in this regard as Toyota's incentives were phased out on September 30, 2007 and Honda's incentives were phased out on December 31, 2008. A full list of incentive amounts can be found in Table 8.1 included in the appendix. The policy ended on December 31, 2010 at an approximate total expense of $1.4 billion to the US government[5].

The most recent incentive provided by the government was the Car Allowance Rebate System (also known as Cash For Clunkers), which gave a tax credit (either $3,500 or $4,500) for the trade-in of less fuel-efficient vehicle for a vehicle of higher fuel-efficiency (several hybrid models were offered). The program was in effect between July 1, 2009 and August 25, 2009. Yet, over 700,000 relatively more fuel-efficient vehicles were sold[6].

This work characterizes the impact that these federal incentives had in promoting the adoption of HEVs and shows how this effect looks like when accounting for the natural pace

[3]Assuming 35% income tax bracket and that all consumers capture the incentive

[4]Press Release, Senator Carl Levin, "Energy Bill Moves Nation Toward Sounder Energy Policy" July 29, 2005.

[5]Obtained by multiplying the incentive amounts in each month by the respective per vehicle model

[6]Department of Transportation Press Release August 26, 2009

of adoption of new technologies.

The literature has studied how different factors shape the preferences of consumers when purchasing HEVs. The first paper by Sallee (2008) performs an in-depth study of the Toyota Prius market. Sallee measures the incidence of tax credits, or consumer's reaction not only to the tax incentive but also to other people's reactions. Specifically, Sallee uses the change in tax incentive from 2005 to 2006 when the Energy Policy Act of 2005 is implemented to investigate strategic shifting of Prius purchases during the fourth quarter of 2005, and concludes that consumers capture all the benefits of the tax incentives. A second paper by Kahn (2007) investigates environmentalism as a characteristic that affects purchasing behavior. Using the number of Green Party voters in an area as a measure of environmentalism from a variety of census data between 1999 and 2005 as well as from the 2001 National Household Transportation Survey data set, Kahn runs a series of regression models to look at differences in consumption and finds that an increase in the share of Green Party voters of 1% decreases the probability that a household owns an SUV (lower fuel economy vehicle) by nearly 20%. Similarly, Sexton (2011) investigate the willingness to pay of Prius owners' to appear environmentally friendly. In this chapter, the authors suggest that individuals who are predisposed to favor environmental goods receive disproportionately greater utility from environmental productseven more so in the case of Priuses, whose unique design garners additional benefit from signalling environmental responsibility. This effect is termed "conspicuous consumption" and is found to be a statistically significant effect among Priuses' owners.

Three papers use econometric analysis to assess the influence of incentives on hybrid sales. Gallagher and Muehlegger (2011) use aggregate national HEV sales data per capita and a fixed effects including as independent variables the presence of High-Occupancy Vehicle (HOV/carpool) lanes, tax credits, sales tax rebates and gas prices while controlling for environmentalism demographics in quarterly periods. Their results indicate that higher tax incentives are associated with more sales, the sales tax incentives having an impact larger than tax credits. HOV lanes, which require either 1 (HOV-1) or 3 (HOV-3) additional passengers besides the driver, exhibit mixed results. The authors find that HOV-1 do not have a significant impact on sales, while HOV-3 are significant in some states. Lastly, they find that a 1% increase in gas prices increases the per capita sales of HEVs between 0.7% and 1%. As one of the first econometric studies of hybrid vehicle incentives, the authors of this work lay the groundwork for many of the explanatory variables used in follow-up regression models. However, these models do not account for positive network externalities in the adoption and diffusion of the new vehicle models (e.g. accounting for the natural growth of new technology), which is likely to positively bias several of their findings. Our study is different in this regard. We explicitly allow the growth in the sales of HEVs to follow a S-shaped curve by including the lag of sales as a dependent variable in the regressions to model the exponential growth in the beginning of the adoption curve.

Another study performed by Chandra et al. (2010) examines the impact of tax rebates on HEV sales in Canada. Their study ranges across all the provinces in Canada, each of which offers different incentives. They generate counterfactual simulations, using a series of models that aggregate rebate values, which they compare to a base case. The latter is measured using existing market data for all HEV models sold in Canada from 2000 through 2006. The authors find that a $1,000 increase in the rebate increased the market share of hybrids by approximately 31-38%. Similar to Gallagher and Muehlegger, this work does not control for the relatively steeper adoption curves one would expect to observe when HEVs are first introduced in the market. Lastly, Diamond (2009) investigates the impact of government incentives for HEVs between 2000 and 2006 by state. He regresses the market share of HEV on vehicle miles travelled per capita, gas, incentives, HOV lane availability, income, and a “green planning capacity” index (a measure of environmentalism) using panel data and both fixed and random effects. This regression is performed on the three most popular hybrid models: Toyota Prius, Honda Civic Hybrid, and Ford Escape Hybrid, which accounted for over 50% of the total share of HEVs during the period of analysis. Diamond’s results reveal that monetary incentives are either non-significant or affect negatively the sales of HEV. The author also performs separate regressions separately for each year and obtains drastically different coefficients from the panel regressions.

In sum, previous work in this field fails to account for network externalities in technology diffusion and adoption. Many studies applied to other technologies have established that these externalities lead cumulative adoption curves to take on S-shapes (Bass, 2004; Griliches, 1957), which consist in exponential growth followed by a change in concavity corresponding to a declining rate of adoption as the technology matures and reaches market saturation (Geroski, 2000; Mahajan and Peterson, 1985; Stoneman, 2002). Many studies have shown that the diffusion of new vehicle technologies, such as hybrid electric vehicles, plug-in hybrid electric vehicles and battery electric vehicles, also follows S-shaped curves (Balducci, 2008; Muraleedharakurup et al., 2010; McManus and Senter Jr, 2009). However, econometric studies investigating the effect of policy instruments in automobile markets have not yet incorporated this effect. As such, they may lead to biased findings for the effect of incentives and other covariates on the sales of HEVs.

In this chapter, we employ an S-shaped growth curve for the sales of HEVs. This, however, requires us to use a spatial-autoregressive model (SAR) with the lag of sales as a dependent variable to capture the autocorrelation in sales over time. This way, we allow the baseline sales from which growth occurs in every period to change over time. The field of spatial econometrics has been well developed for over thirty years (Anselin, 2010) with a variety of established methods for model estimation (Anselin, 2006; Anselin et al., 2008; LeSage, 2008). Our estimation procedure employs a Generalized Method of Moments (GMM) estimator, in which we use deeper lags of our lagged dependent variable as instruments, a method that has been developed over the last decade (Conley, 1999; Kelejian and Prucha, 1998; Lee, 2007).

Jaffe and Stavins (1995) study the effect of policy instruments on technology diffusion. They employ a lagged dependent variable to control for adoption of thermal insulation in new home construction. Their econometric estimation explicitly estimates the lagged dependent variable (measuring efficiency) as a parameter in the shape of the adoption curve. Similarly, Hannan and McDowell (1990) employ a lagged dependent variable in order to accommodate the growth of banking ATMs as a control. Their specification is slightly different from the model employed in our study, as they use two lag periods. In both papers, the authors find the coefficients on the covariates to be statistically significant using lagged dependent variables as controls. They conclude that this approach is the most appropriate to account for the correct shape of the adoption curve for new technologies.

The rest of the chapter is organized as follows: section 2.2 presents the data used in the analysis, section 2.3 explains the methodology used, section 2.4 shows and discusses our results and section 2.5 concludes discussing applications of this study.

2.2 Data

2.2.1 Vehicle sales data

We use national monthly sales of HEVs and of other light duty vehicles by make and model from 2000 through 2010. Monthly sales data of HEVs were obtained from the "Data Center Archives" of www.autonews.com for the period January 2000 to December 2005 and from the "Hybrid Market Dashboard" of www.hybridcars.com for the period January 2006 to December 2010. Sales of light duty passenger vehicles by month, make and model were parsed from the former data source for the whole duration of the panel. Figure 2.2 shows the total monthly fleet sales as well as the monthly sales of HEVs.

HEV sales are dominated by the Toyota Prius, which match all other HEV sales combined since the introduction of HEVs in 2000 until mid-2006. While overall sales of light duty-vehicles remained relatively constant between 2004 and 2008, the sales of HEVs increased significantly over these years. Following the spike in oil prices in the summer of 2008, overall vehicle sales decreased 35% until mid 2010. Sales of HEVs decreased only 18% during these

[7] Compiled from www.autonews.com and www.hybridcars.com

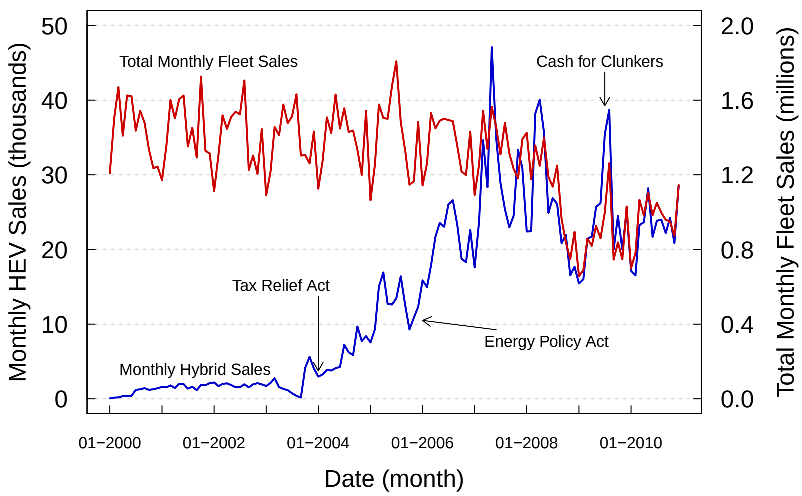


Figure 2.2: Hybrid electric vehicle and total fleet monthly sales in the US from January 2000 to December 2010[7]

two years and therefore the market share of HEVs has been mostly increasing since 2004 as Figure 2.3 depicts. Sales of HEVs were highest in May of 2007, when a record of Priuses were sold, possibly due to a massive advertising campaign led by Toyota during the first quarter of 2007[8][9]. Both in in June and July of 2009, there was another sudden spike in the sales of HEVs, likely attributable to the Cash for Clunkers Program. Figure 2.2 also shows the implementation dates for the three federal incentives that incentivized HEVs purchases between 2000 and 2010: the Tax Relief Act of 2004, the Energy Policy Act of 2005, and the Cash and Clunkers in July and August of 2009.

[8]Maynard, Micheline. "With waiting lists filled, Toyota starts advertising the Prius". The New York Times. February 8, 2007. http://www.nytimes.com/2007/02/08/business/worldbusiness/08iht-toyota.4526592.html

[9]Isidore, Chris. "Prius' new option: Incentives for buyers". CNN Money. February 8, 2007. http://money.cnn.com/2007/02/08/news/companies/prius_sales/index.htm

[10]Compiled using data from: www.autonews.com and www.hybridcars.com

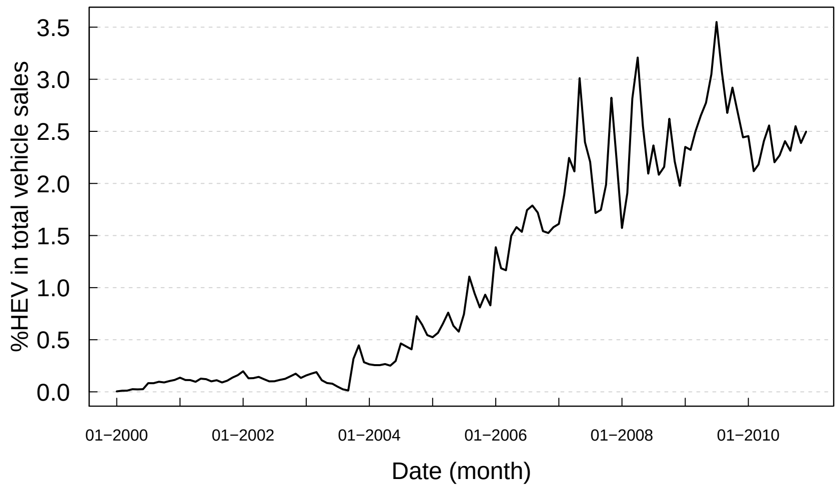


Figure 2.3: Percentage of hybrid electric vehicle monthly sales[10]

2.2.2 Policies: Tax Relief Act, Energy Policy Act, and Cash for Clunkers

Our main interest is to study whether the introduction of the Energy Policy Act of 2005 accelerated the sales of HEVs. To this end we code a variable, called $EPACT_{it}$ that equals the dollar incentive provided to vehicles of model i at time t. This variable is zero for all models before the Energy Policy Act was implemented as well as for all models to which the Act does not provide an incentive. Table 8.1 in the appendix shows how these incentives changed across hybrid models and over time. Coding $EPACT_{it}$ simply as a dummy variable, indicating whether the Energy Policy Act of 2005 applied to vehicles of model i at time t, yields qualitatively similar results to the ones presented later in this work.

We also control for the introduction of other policies that might have had an impact on the sales of vehicles, such as the Tax Relief Act of 2004 and the Cash for Clunkers program of 2009. For this purpose, we code a dummy variable, called $Taxrelief_{it}$, indicating whether the Tax Relief Act applies to vehicles of model i at time t. Finally, we add a dummy variable called $Cashforclunkers_it$ indicating whether this program applied to vehicles of model i at time t. The Cash for Clunkers program applied to some models during July and August 2009, thus this variable is always zero for all models for all other months in our panel.

2.2.3 Other data

Other data related to vehicle sales

We control for the following factors that might impact the sales of certain types of models:

- *Advertising campaign by Toyota*: From January through May of 2007, Toyota lunched a massive advertising campaign, which might have increased the sales of Prius. To capture this potential effect we introduce a dummy variable, called $priusad_{it}$, which equals 1 for this model during these months.

- *Models discontinued by manufacturers*: Some manufacturers discontinued certain vehicle models during our period of analysis. To account for these cases we included a dummy variable, called $productionstoppage_{it}$ indicating whether model i has been already discontinued at time t. This variable should capture sharp decreases in the sales of these vehicles.

- *Vehicles produced domestically or imported*: Imported vehicles typically sell in different amounts than their domestic counterparts. To capture this effect, we coded a dummy variable, called $import_i$, indicating whether model i is imported.

Macro-economic variables[11]

We added the following macro-economic variables in the models to account for changes in the economic climate throughout our panel:

- *Unemployment*[12]: we control for the unemployment rate because, everything else equal,

[11] All variables in nominal values for consistency

[12] Data from: U.S. Department of Labor, Bureau of Labor Statistics. data.bls.gov/timeseries/LNS14000000

a higher unemployment rate should translate into less disposable income which, in turn, would typically lead to fewer sales of vehicles.

- *Gas prices*[13]: we control for gas prices because a high gas price may lead consumers to substitute towards more fuel efficient vehicles, such as hybrids. However, we note that consumers may not necessarily respond quickly to increases in gas prices. To account for this we introduce lagged gas prices in the regression models. Later in this chapter we report results with gas prices lagged six-month, which provide the highest statistical significance for this covariate. Using other lags for the price of gas does not change our results.

We also tested numerous other macroeconomic variables for robustness purposes, such as GDP, income and interest rates; none of which significantly altered our final results.

Summary statistics

Table 2.1 below displays the summary statistics for the main variables used in this study. US vehicle monthly sales peaked at 52,400 for the best-selling ICE vehicle model.This is only considerably higher than the highest monthly sales of the Toyota Prius, which peaked at 24,000 in May 2007. At the lowest, there were models (that were not discontinued) that sold no vehicles during an entire month. This typically happens to some sports and luxury vehicles. The average US sales per model are lower than the HEV sales per model because there are much fewer hybrid models and a significant share of the non-hybrid models do not sell many units per month.

2.3 Empirical Strategy

We perform econometric regressions to understand the effect of the incentives for hybrids in the Energy Policy Act of 2005 on the sales of HEVs. We study this relationship for

[13] U.S. Energy Information Administration. Monthly Reviews.

Table 2.1: Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Monthly US Vehicle Sales (by model)	3,540	5,500	0	52,400
Monthly HEV Sales (by model)	1,520	2,950	0	24,000
Tax Relief Act of 2004*	0.00323	0.0567	0	1
Energy Policy Act of 2005	49.6	314	0	3,400
Cash for Clunkers*	0.0172	0.13	0	1
Import*	0.567	0.496	0	1
Production Stoppage*	0.103	0.304	0	1
Prius Ad Campaign*	0.00021	0.0145	0	1
Unemployment Index	5.96	1.84	3.8	10
Gas Prices	2.42	0.611	1.35	4.14
Hybrid*	0.049	0.216	0	1

Observations: 23,843; The total number of models is 431, from which 33 are HEVs
* indicates a dummy variable

monthly vehicle model sales from 2000 through 2010 using the control variables described in Section 2.2.3 (imports, production stoppage, Prius advertising campaign, unemployment and gas prices). We show that the EPACT had a statistically significant non-linear effect with higher incentive amounts leading to a disproportionately larger effect on sales. We also show that a traditional fixed effects model, which does not account for the S-shaped curve for technology adoption, finds a severely positively biased effect for this incentive.

We capture the initial exponential growth of sales in adoption by adding a lagged dependent variable to the regression, as follows:

$$\ln\left(S_{it}\right) = \alpha + \pi \ln\left(S_{i(t-1)}\right) + \beta\left(EPACT_{it}\right) + \gamma\left(x_{it}\right) + u_i + \varepsilon_{it} \tag{2.1}$$

i represents a vehicle model and t represents the time period ranging from 1 through 132 (representing each month from January 2000 through December 2010). S_it represents monthly vehicle sales by model. $EPACT$ represents the dollar incentive provided per vehicle over its allotted period of implementation (see Table 8.1 in the appendix). x includes control variables, as described in Section 2.2.3, and variables that control for other policies, as description in Section 2.2.2, which may influence the consumers' decisions to purchase a vehicle. In this regression, all of the non-dummy variables (unemployment and gas prices) were transformed by using the natural log. Finally, u_i is a vector of unobserved vehicle model specific time constant effects and ε_{it} represents the unobserved error term.

The addition of lagged sales as an independent variable in our setup violates strict exogeneity, which is an essential assumption of Ordinary Least-Squares (OLS). In order to overcome this challenge, we follow Arellano and Bond (1991) and use a Generalized Method of Moments estimator (GMM) to estimate the fixed effects regression in the Equation (2.1). We instrument previous lags ($S_{i(t-1)}$) using two sets of different lagged instruments and we use the J Hansen statistic to verify that our model is not over specified.

One of the benefits of using panels or differences across vehicles in regression models is the ability to implicitly capture unobserved characteristics inherent to each vehicle model in the fixed effects term, u_i, or difference them out (using first differences). For this reason, vehicle characteristics such as price (captured by the manufacturers suggested retail price) or fuel economy, which do not change much over time, are not explicitly included in our models but their effects are still accounted for[14]. Also, we cluster standard errors at the vehicle model level to account for serial correlation in our data.

In addition, we suspect that the $EPACT$ behaves non-linearly, with a particularly larger effect for vehicles provided with a larger incentive. Thus, we also provide results by splitting $EPACT$ into two categories: above and below its approximate average amount ($1,000). The resulting model is as follows:

$$\ln\left(S_{it}\right) = \alpha + \pi \ln\left(S_{i(t-1)}\right) + \beta_1\left(EPACT_{it}^{\text{high}}\right) + \beta_2\left(EPACT_{it}^{\text{low}}\right) + \gamma\left(x_{it}\right) + u_i + \varepsilon_{it} \quad (2.2)$$

$EPACT^{\text{high}}$ represents the dollar amount of incentive by vehicle for any hybrids receiving over $1,000 of incentive and $EPACT^{\text{low}}$ represents the dollar amount of incentive by vehicle

[14]For all HEV models, the manufacturer's suggested retail price (MSRP) and fuel economy (fueleconomy.gov) stay relatively constant during the lifetime of one generation of vehicle model (5-8 years). The largest observed increase/decrease was less than 5% and both variables typically dropped out of the regression results.

for any hybrids receiving under $1,000 of incentive.

2.4 Results and analysis

2.4.1 Understanding the effect of EPACT incentives on sales

Table 2.2 displays the main regression results. Models (1) and (2) correspond to Equations (2.1) and (2.2) in Section 2.3, respectively. Dummy variables for the months have been used in each case. In model (1) we show that the Energy Policy Act had a positive and statistically significant effect on the sales of HEVs. Sales increase by 0.0046% per dollar of incentive, on average. When we split the EPACT into a high and low incentive amount (model (2) in Table 2.2), we find that only $\text{EPACT}^{\text{high}}$ is statistically significant. The effect of EPACT is therefore confined to hybrid vehicles receiving incentives over $1,000. The significance of the EPACT impact disappears for vehicles with small incentive amounts. The EPACT for vehicles with large incentive amounts captures, both in statistical significant as well as in magnitude, the effect obtained in model (1). Qualitatively, this means that consumers may not be easily swayed towards purchasing a hybrid vehicle when only a small incentive is present given the relatively large monetary premium associated with HEVs. We note that the J Hansen statistic indicates that our models are not overspecified, which increases our confidence in the sets of instruments used and thus in our findings.

2.4.2 Bias from using traditional fixed-effects

We compare the results obtained in the preceding section using the ArellanoBond estimator to the ones obtained using fixed-effects without lagged sales. Full results for the latter are shown in the appendix in Table 8.2. This comparison, depicted in Figure 2.4, highlights the importance of accounting for network externalities in the diffusion of HEVs. The effect of the EPACT remains positive and statistically significant with fixed effects without lagged sales but now each additional dollar of incentive provided increased sales of 0.031%. This

Table 2.2: Effect of EPACT on ln(sales) using fixed effects regression with a generalized method of moments estimator (GMM) to account for exponential growth in the diffusion of HEVs, also splitting EPACT into above and below its average amount ($1,000).

	(1)	(2)
Variables	lnsales	lnsales
taxrelief	-0.0143	-0.0173
	-0.074	-0.0741
epact	**4.60e-05***	
	-2.35E-05	
epactlow		**-1.41E-06**
		-6.35E-05
epacthigh		**4.54e-05***
		-2.37E-05
cashforclunkers	-0.492***	-0.491***
	-0.0958	-0.0959
import		
prodstop	-0.680***	-0.680***
	-0.0583	-0.0583
priusad	0.206	0.227
	-0.145	-0.143
lnunemp	-8.085**	-8.095**
	-3.286	-3.286
lnunemph	0.168**	0.166**
	-0.081	-0.0813
lngas6	-3.199	-3.18
	-6.628	-6.628
lngas6h	0.604***	0.596***
	-0.18	-0.18
L.lnsales	0.908***	0.908***
	-0.00861	-0.00861
L.lnsalesh	-0.0377	-0.0368
	-0.0271	-0.0271
Monthly time dummies	Yes	Yes
Observations	20,787	20,787
R-squared	0.917	0.917
Number of Groups	335	335
Instruments (lags used)	sales(1-6)	sales(1-6)
Hansen J Stat	0.112	0.108

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

result is robust when using other combinations of control covariates. The inclusion of the lagged dependent variable to account for exponential growth reveals the difference in results based on assumptions of functional form to estimate the effect of policy instruments on the diffusion of new technologies, such as the EPACT. Our model indicates a difference in effect from previous studies of an order of magnitude.

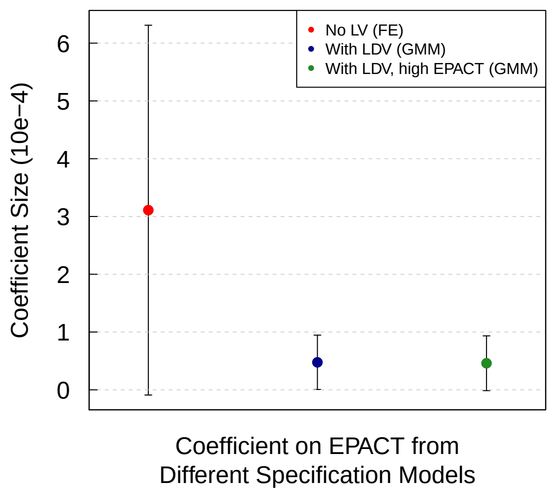


Figure 2.4: Coefficient size of Energy Policy Act of 2005 using fixed-effects and generalized method of moment estimators, with 95% confidence intervals. LDV = lagged dependent variable; FE = fixed-effects; GMM = general method of moments.

2.4.3 How did the EPACT affect the sales of different vehicles?

2.5 shows the impact of the EPACT on the sales of vehicles across different vehicle types using the results obtained with the ArellanoBond estimator. This figure reveals that, for example, at the full incentive amount of \$3,150, the Toyota Prius experienced a 15% increase in sales over the vehicles that would have been sold in absence of such incentive. Our results indicate that EPACT has statistically significant effect on the different models sold, through varying in magnitude from 3% to 20%.

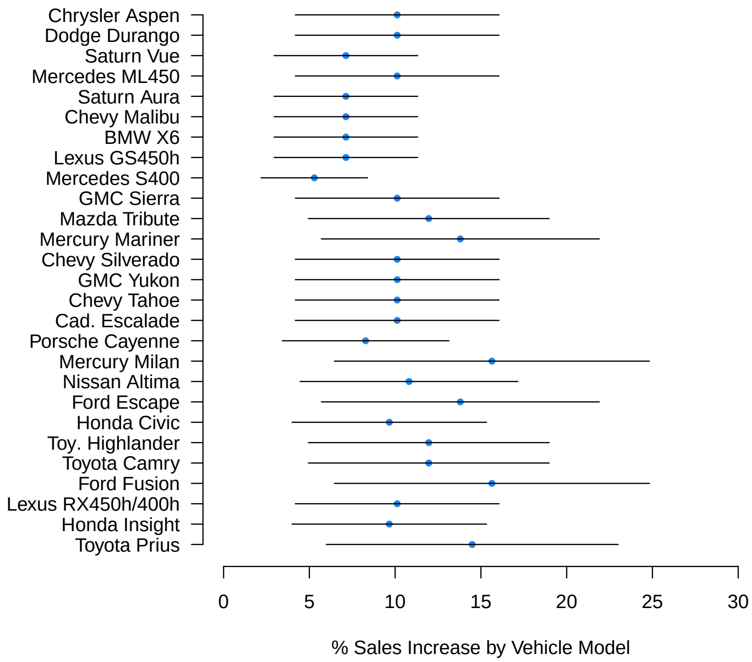


Figure 2.5: Estimated increase in sales due to the Energy Policy Act of 2005 (when incentive active and over $1,000) by vehicle model and associated 95% confidence intervals.

2.4.4 Insights from control variables

The results from our control variables provide additional insights into the transportation market and are thus worth analyzing. For example, higher levels of unemployment are associated with lower overall vehicle sales, as one would expect. In fact, 2.6 shows a sharp decline in vehicle sales in 2008 when the unemployment rate rose significantly. Our findings indicate that a 1% increase in the unemployment index is associated with about an 8% decrease in the sales of cars, on average. The effect of unemployment on the sales of hybrid vehicles is statistically significant but only negligibly lower.

Gas prices are not statistically significant for ICE vehicles in the GMM model estimations. However, the interaction of gas prices with the hybrid vehicle dummy yields a positive elasticity of about a 0.6%. These results seem to indicate that rising gas prices may not necessarily dissuade consumers from purchasing ICE vehicles, but that more hybrid vehicles are purchased in the months following high gas prices.

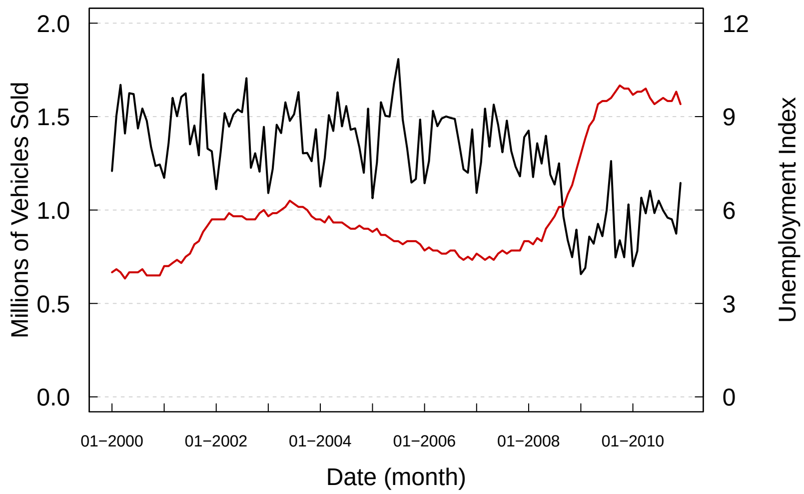


Figure 2.6: Comparison of vehicle sales with unemployment index. Figure constructed by the authors using data from Autonews.com and the Bureau of Labor Statistics.

2.5 Conclusions

This chapter aims at understanding the impact that federal incentives had in promoting the adoption of HEVs. Using national data on vehicle sales between 2000 and 2010, we find that the Energy Policy Act of 2005 had a positive and statistically significant effect on the sales of hybrid vehicles. However, we also show evidence that only sufficiently large incentive amounts yield an effect on sales. Sales of hybrid vehicles increased by 0.0046% per dollar of incentive but only when the latter was above $1,000.

Another goal of this study is to understand the importance of accounting for network externalities in the diffusion of technology. Network externalities result in an initial natural exponential growth in adoption that occurs even if no policy incentives are in place. Comparing fixed-effect results with and without lagged sales as a control variable, we show that failing to account for this growth overestimates the effect of EPACT in one order of magnitude. However, using the latter approach requires us to resort to a generalized method of moments (GMM) using deeper lags of sales as instrumental variables. Our results show a large difference in incentive effects of existing studies as a result of our functional form assumption we use to capture the adoption of HEVs.

Finally, it should be cautioned that the results obtained in this study are at a relatively low level of resolution given the constraints associated with the data available. We could not conduct an analysis at the regional level, which would shed more light on the role of policy incentives on the adoption of HEVs. It may well be the case that only combinations of incentives, including federal, state and local incentives, can cause substantial changes in consumer behavior. Such combination of incentives could help explain why there is a proportionally higher registration of hybrids in states such as California, Washington and Virginia.

Chapter 3

How will we fund our roads? A case of decreasing revenue from electric vehicles

3.1 Introduction

There are over 4 million miles of interstate highways, freeways, expressways, and local roads in the United States[1]. The transportation infrastructure is costly to build and even costlier to maintain: in 2010 approximately $4 billion was spent on the construction of new highways and bridges and $19 billion was spent on maintenance of existing highways and bridges by the federal government[2]. Similarly, state-level departments of transportation fund transportation infrastructure projects and maintenance on a regional basis to the amount of about $90

Abbreviations: Hybrid Electric Vehicle (HEV), Internal Combustion Engine (ICE), Greenhouse Gas (GHG), Cash for Clunkers (C4C), Lagged Dependent Variable (LDV), Corporate Average Fuel Economy (CAFE), National Highway Traffic and Safety Administration (NHTSA), Environmental Protection Agency (EPA), One National Program (ONP)

[1] U.S. Department of Transportation: Federal Highway Administration. Highway Statistics 2010, Table HM-20. http://www.fhwa.dot.gov/policyinformation/statistics/2010/hm20.cfm

[2] U.S. Department of Transportation: Federal Highway Administration. Highway Statistics 2010, Table FA-10. http://www.fhwa.dot.gov/policyinformation/statistics/2010/fa10.cfm

billion in 2010[3]. Expansion of road networks and other transportation infrastructure means that these costs have increased historically, a trend that is likely to continue in the coming years. Figure 3.1 shows the level of total federal revenue and spending from 1985 until 2012. Over the course of the last few year, expenditures have exceeded revenue generation. One exception was 2010, where an infusion of funds from stimulus funding occurred.

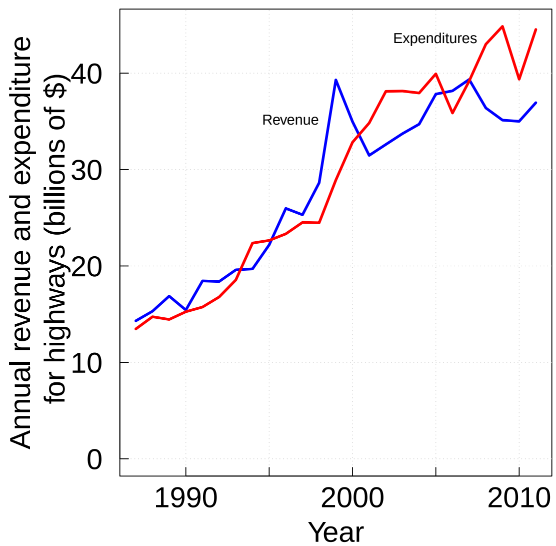


Figure 3.1: Historical Federal Highway Revenues and Expenditures (real dollars) from 1985 to 2012. Figure produced by the authors using data from U.S. Department of Transportation Highway Statistics 2010.

The adoption of electric vehicles presents an interesting problem for revenue generation. Since a relatively large portion of fees are collected through vehicle use by way of taxes on gasoline (50%-70%), large-scale adoption of EVs would result in a decline in revenue generation since they use little to no gasoline as fuel. The number of EVs sold in the future is required order to estimate potential revenue losses.

Figure 3.2 shows an increasing trend in both the quantity and availability of EVs since their first introduction into the automobile market in December of 2010. The most popular vehicles sold are the Chevrolet Volt (PHEV) and the Nissan Leaf (BEV) though the Toyota

[3]U.S. Department of Transportation: Federal Highway Administration. Highway Statistics 2010, Table SF-2. http://www.fhwa.dot.gov/policyinformation/statistics/2010/sf2.cfm

Prius (PHEV) and Tesla Model-S (BEV) have been recently gaining traction in sales as well. The variance in sales follow cyclical seasonal trends in vehicular sales, though the overall growth of many individual models are far outpacing average vehicle model growth in the industry.

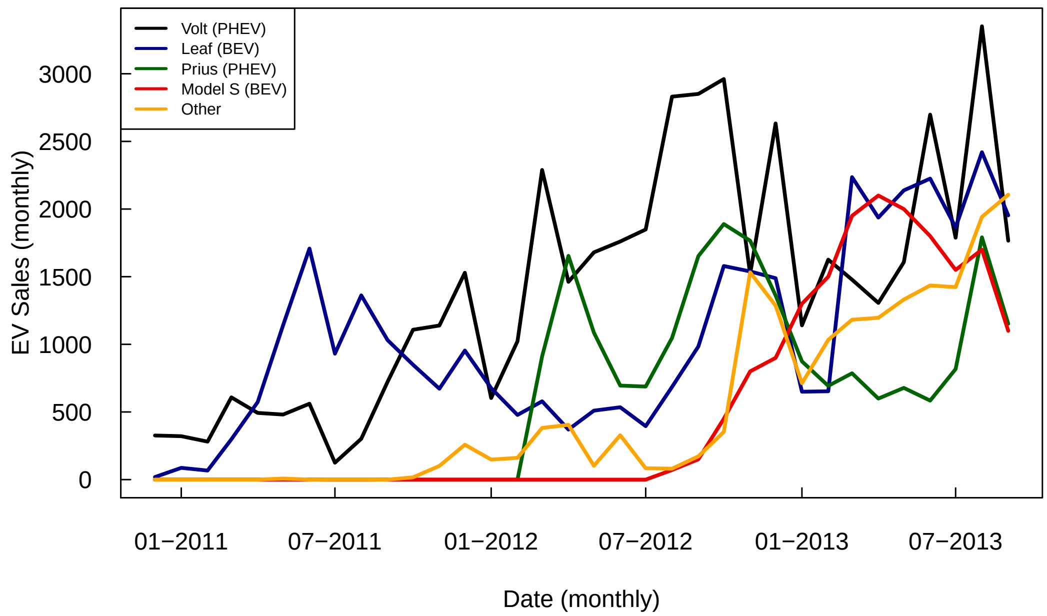


Figure 3.2: Monthly sales figures for electric vehicles by model. Figure produced by the authors using data from http://www.hybridcars.com Hybrid Market Dashboard.

The increasing trend in EV sales can be seen above in Figure 3.2 and has grown in size by approximately double every year. Though this trend is not expected to continue, the EIA has made projections for EV adoption over the next decade in their Annual Energy Outlook (EIA)report as seen in Figure 3.3. AEO reports from the EIA are generally used by energy modellers as baseline scenario for their assumption. As many other modellers, we will pursue the same assumption. However, we not that projections of sales by vechile type are highly uncertain. For example, as shown in Figure 3.3, the AEO report that was published in 2013 does not provide a good alignment with 2012 historical sales.

A number of reports have recently been produced by agencies such as the Congressional Budget Office and the American Society of Civil Engineers that discuss declining sources

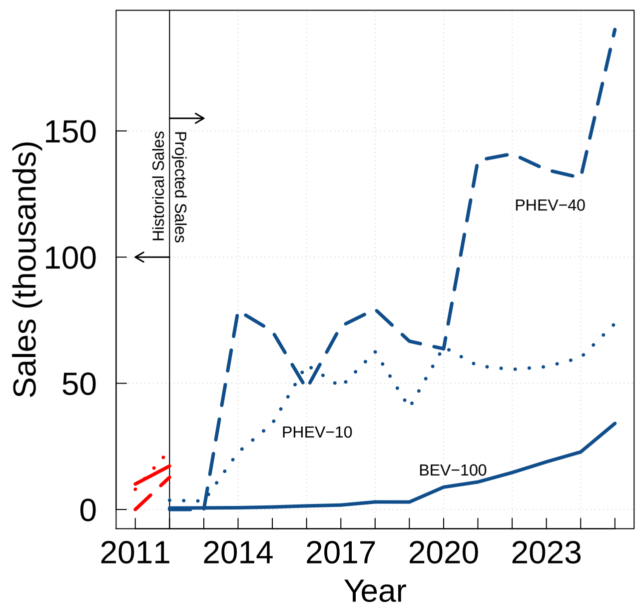


Figure 3.3: Projections of electric vehicle sales through 2025 by the Energy Information Agency Annual Energy Outlook 2013. Discontinuity due to differences between actual sales and projected sales by the EIA. Figure produced by the authors using data from U.S. Department of Energy/Energy Information Administration, *Annual Energy Review 2013*. DOE/EIA-0383(92). Washington, DC (2013).

of funds for critical infrastructure such as in transportation (Bradley et al., 2011; Musick, 2010; Hermann, 2009; Coussan and Hicks, 2009). Krishen et al. (2010) and Watts et al. (2012) highlight shortcomings of the gasoline use tax, particularly with decreased feasibility in funding opportunities as high fuel efficient vehicles are adopted. Dutta and Patel (2012) and Schank and Rudnick-Thorpe (2011) also discuss implications of different policy designs to generate revenue for transportation infrastructure in light of many of the issues facing the US.

Our work contributes to the body of literature by specifically quantifying the monetary impacts of electric vehicles (including plug-in hybrids (PHEVs) and fully battery electric vehicles (BEVs)) adoption within the US, both in the past as well into the future using projections from the Energy Information Agency (EIA). The remainder of the chapter is organized as follows: in section 3.2 we provide a description of the data we use to estimate the magnitude of EV adoption. In section 3.2 we also provide an overview of the approach we use to calculate the cost figures. In section 3.3 we provide the results and analysis and section 3.4 ends with a presentation of the findings of our work and policy implications.

3.2 Data & Methods

3.2.1 Breakdown of current revenues and expenditures by state

Funding for transportation infrastructure is derived at three levels: federal, state, and local. The federal funding is specifically used for interstate highway construction and maintenance and comes from apportioned budgeting through Congress (such as funds from the stimulus package) as well as a use-fee flat tax on gasoline at 18.4¢ per gallon. State-level data were accumulated from states' respective department of transportations and legal rules for vehicle fees. These fees are used to fund state-level transportation projects as well as local road construction and maintenance. State fees consist of a variety of use and fixed taxes including an additional gasoline tax, title fees, registration fees, and inspection fees. Registration fees are typically charged at an annual or biannual basis and are typically flat or a function of vehicle weight or age. A description of state level charges can be found in the Appendix 8.2, Table 8.3. In the Section 3 we provide a breakdown of revenues and spending by state for each of the major categories.

3.2.2 Lifetime fees for for specific vehicle models in each state

We estimate the total lifetime fees paid at the margin for a specific vehicle model by aggregating the different components of fees outlined in the Appendix in Table 8.3. To estimate the average fuel consumption over the lifetime of the vehicle, we calibrate vehicle use behavior with a standardized annual vehicle miles travelled of 12,500 miles and a lifetime of 12 years[4] for all states in Table 8.3. The results are spatially portrayed on a state-by-state basis as well as broken down by components of funding sources in order to identify which fees are

[4] Average values for vehicle use according to NHTSA report: Lu (2007)

primarily responsible for decreases in overall revenue for EVs. Comparisons are based on fees calculated on a state-by-state basis using the characteristics in Table 3.1 as new cars that progressively age in our analysis.

Table 3.1: Vehicle Characteristic Inputs (MY 2013)

Vehicle Model	Toyota Camry	Honda Civic	Ford F-150	Nissan Leaf	Toyota Prius	Chevrolet Volt
MSRP ($)	22,235	18,165	24,070	21,300	32,000	34,185
Curb Weight (lb)	3,190	2,740	4,685	3,291	3,165	3,786
Gas Fuel Efficiency (mi/gal)	28	32	20	NA	50	37
Technology	ICV	ICV	ICV	BEV	PHEV-10	PHEV-40
Horsepower	178	140	302	107	98	149

3.2.3 Assessing and projecting aggredated funding deficits

To calculate aggregate funding deficits, we use historical (for 2010-2013) and projected (for 2013-2025) vehicle sales broken down by vehicle model. Estimates for funding are run through several policy alternatives in order to determine which state-level policies are most amenable to maintaining revenue flow for increasing levels of electric vehicle adoption.

We use Toyota Prius PHEV for the PHEV-10, the Chevrolet Volt for the PHEV-40, and the Nissan Leaf for the BEV-100 as representative vehicles. The proportion of time spent in electric drive mode is based on assumptions from the EPA with the Prius PHEV being 29% and the Chevrolet Volt being 66%[5].

In order to distribute the projected sales over the 50 US states, we proxy sales based on average distributions of Toyota Prius (HEVs) over the past decade as a superior representative to EV sales than the average vehicle model sold in the US.There is a substantial difference in state-level market share of Toyota Priuses compared to the average vehicle, and by proxying with the Prius we are better able to capture spatial consumer dynamics favoring "greeness".

[5]2013 Fuel Economy Datafile from the Office of Transportation & Air Quality from the US EPA at http://www.fueleconomy.gov/feg/download.shtml

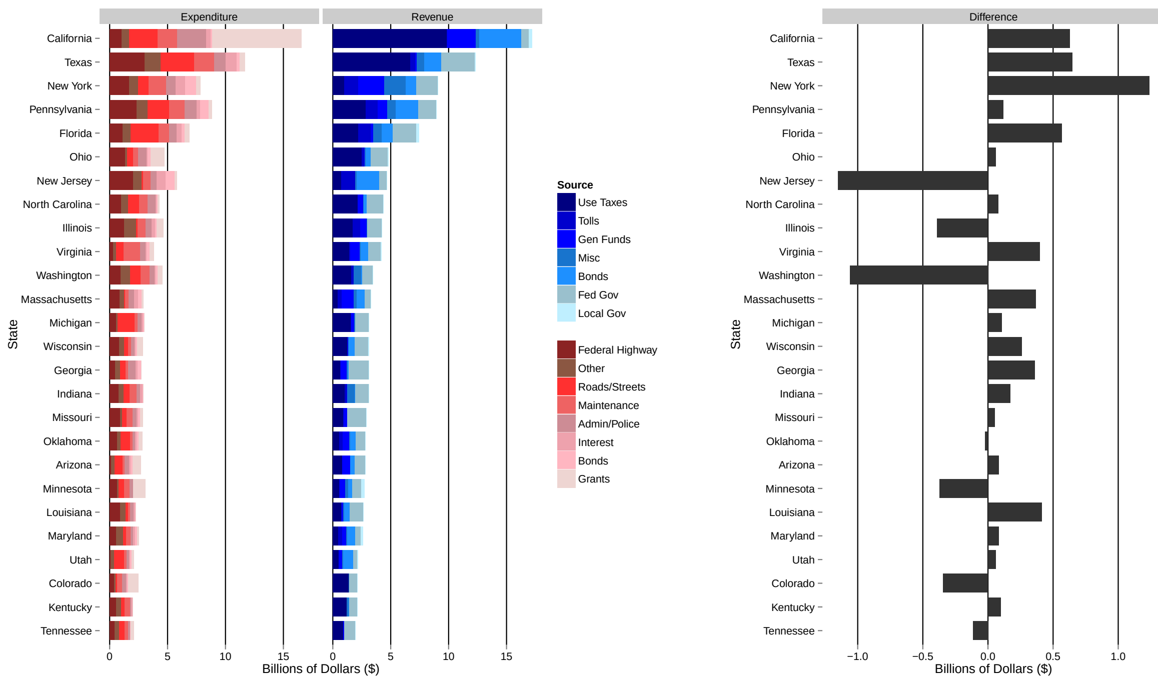
3.2.4 Policy strategies to overcome the funding deficit arising from EV adoption

We estimate alternative policy options specifically for EVs that can help overcome the decreases in revenue generation in the status quo. The first option is charging an annual registration fee that is based on the percentage of MSRP of the vehicle, this helps overcome decreases from use fee revenues since EVs typically have a higher initial capital cost relative to traditional ICVs. We conduct an analysis across distribution of sales by state while parametrically varying the percentage of MSRP being charged. The baseline of comparison in all cases is a replacement of the Toyota Camry. Similarly, we also consider a policy option that charges based on a use fee tax and conduct an analogous sensitivity analysis with while varying the dollars per mile charge.

3.3 Results and Discussion

3.3.1 Breakdown of current revenues and expenditures by state

Figures 3.4 and 3.5 break down the components of revenue generation and expenditures for transportation infrastructure in 2011 by state. The funds for the vehicle infrastructure come from a variety of sources including vehicle license and registration fees, toll road fees, inspections, titling, gasoline fuel taxes, and a number of other minor sources. Transportation departments are facing or will likely be facing deficits. We examine the effect of a changing vehicle fleet on the revenue generating capability of transportation departments in the United States. There is a potentially large decrease in gasoline tax revenue due to the increasing adoption of alternative fuel vehicles (AFVs) such as plug-in hybrids or full battery electric vehicles combined with the mandated fuel efficiency requirements from the Corporate Average Fuel Economy (CAFE) standards. Given the different tax and fee structures accross states, as well as different vehicle fleet mixes, the revenues (and revenue losses) likely incurred by each state will differ widely. We estimate the lifetime fees associated with new alternative fuel vehicles across all 50 states in the US, as well as examine which state fee structures are most amenable to maintaining budgets amidst lower gasoline consumption at the margin.



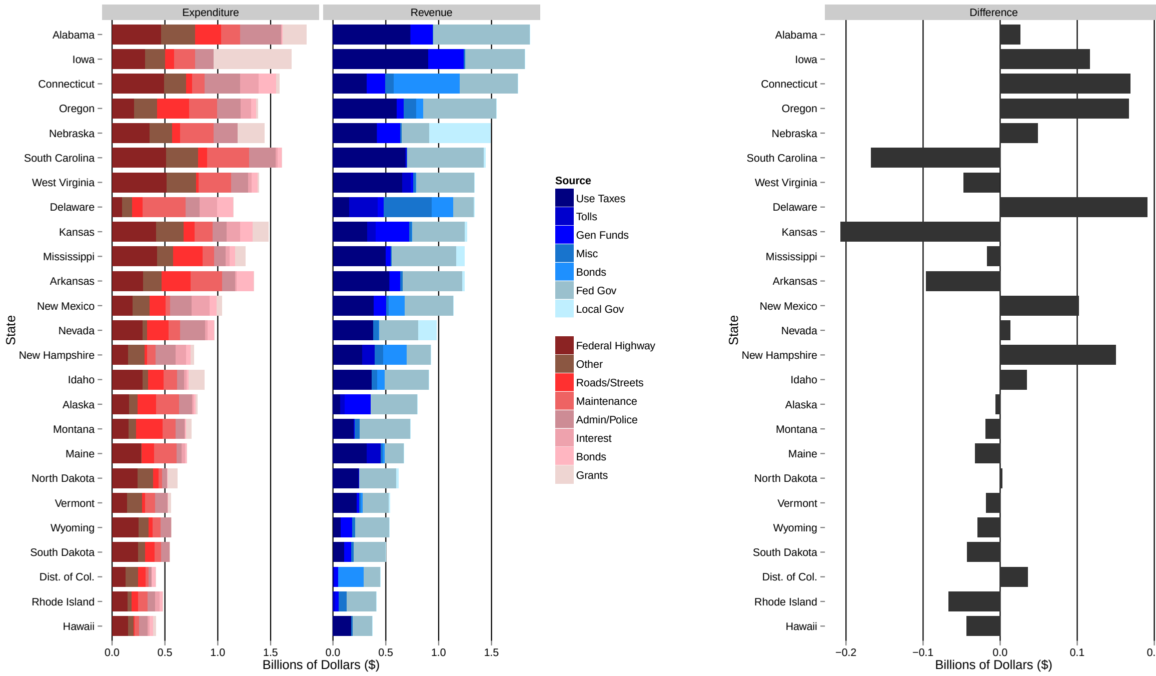
(a) Breakdown of revenues and expenditures

(b) Difference between revenue and expenditures

Figure 3.4: Revenue and expenditures for 25 top grossing states in 2011 (highest revenue at approximately $15 billion). In (b), positive values indicate higher revenues than expenditures and negative values indicate higher expenditures than revenues.

3.3.2 Lifetime fees for for specific vehicle models in each state

The results for revenue generation vary across the country because of differential state tax/fee policies. For standard midsize and compact vehicles as in Figures 3.6(a) and 3.6(b), most states gain approximately $2000 to $4000 in revenue over the lifetime of the vehicle with typically over half of the fees being accrued from fuel taxes. Consider the states of California and Colorado, the former of which has relatively high fees due to its fuel tax and Colorado,



(a) Breakdown of revenues and expenditures

(b) Difference between revenue and expenditures

Figure 3.5: Revenue and expenditures for 25 bottom grossing states in 2011 (highest revenue at approximately \$1.8 billion). In (b), positive values indicate higher revenues than expenditures and negative values indicate higher expenditures than revenues.

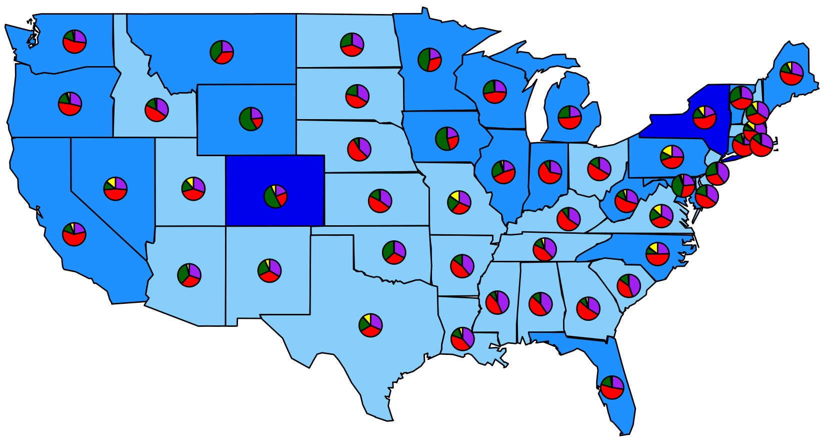
which has high fees due to its registration fee as a function of MSRP. The Camry fees are slightly higher for Colorado at \$4600 compared to \$4200 in California.

For less fuel efficient vehicles, such as the light-duty F-150 truck seen in Figure 3.6(c), revenue generation is substantially higher from \$3000 to \$6000 over the lifetime of the vehicle. The share of revenue generation from fuel taxes typically increases across all states because of the large amount of gasoline consumption. For ICVs, most states generate at least half to two-thirds of their revenue from fuel taxes, a source of revenue that is significantly diminished for EVs. The state fees in California and Colorado are quite similar at about \$5800 between both states, where the inefficient fuel economy in California compensates for the high registration fees in Colorado.

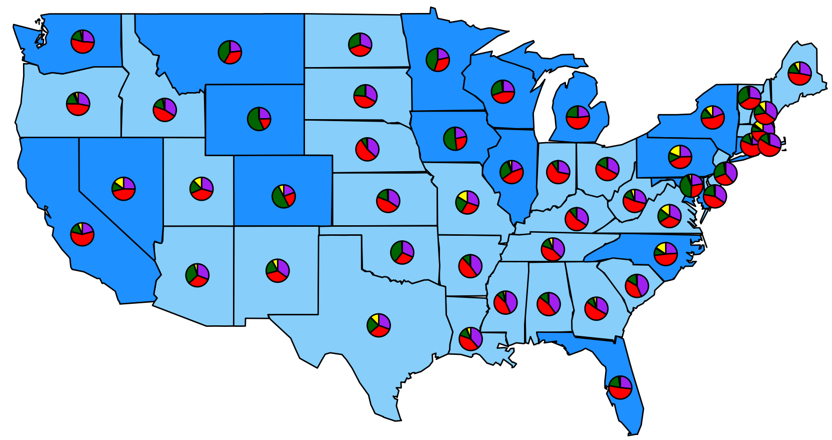
As shown in Figure 3.7(a), revenue generation from the Nissan Leaf is substantially lower than conventional ICVs with a range less than half of the Camry or Civic at around \$400 to

$1300. Most noticeably from the breakdown of components of fees, there are no fuel taxes because of the fact that the electric drive in the Leaf does not consume any gasoline. Now the difference between California and Colorado are quite significant: California cannot rely on its high fuel taxes, resulting in a revenue collection of only $600 over the lifetime of the Nissan Leaf in comparison to $3100 in Colorado.

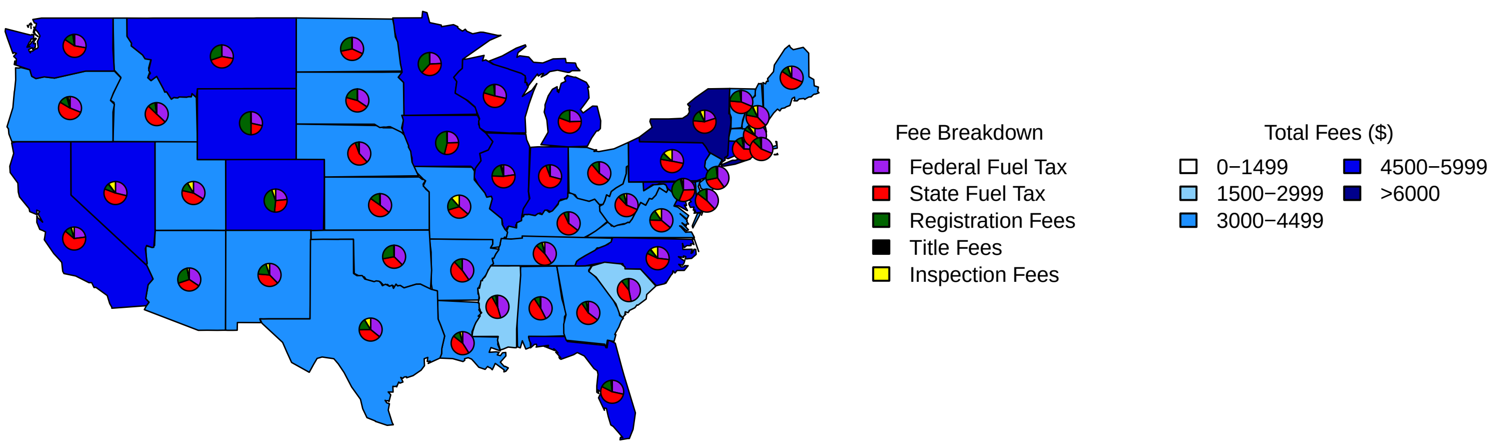
The revenue generation for PHEVs is higher than BEVs such as the Nissan Leaf as seen in Figures 3.7(b) and 3.7(c) with a range from $1500 to about $2700, which is still at the lower end of comparable ICVs. For these plug-in hyrid electric vehicles, the proportion of fees from fuel taxes is substantially lower because of operation of the eletric drivetrain that does not require any gasoline. Once again, the decrease in revenue generation is substantially lower in states with MSRP based registration fees. Colorado's lifetime fees for the Prius and Volt are $4000 and $4800 respectively compared to California's fees of $2400 for both vehicles, representing around a 50% decrease in revenue generation for both vehicle models.



(a) Toyota Camry (Midsize ICV model)

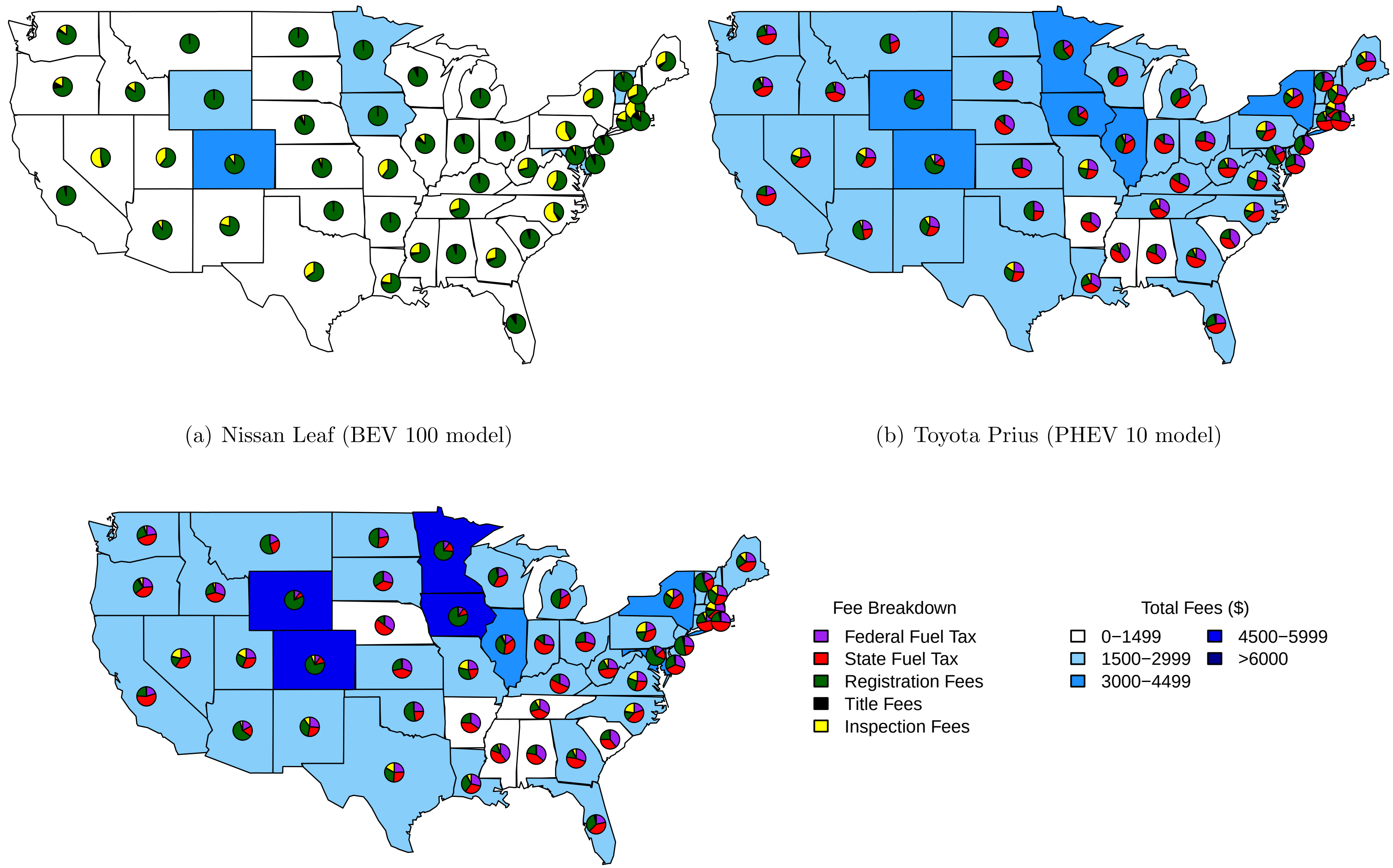


(b) Honda Civic (Compact ICV model)



(c) Ford F150 (Light-duty truck ICV model)

Figure 3.6: Lifetime fees for ICVs by state. The color-code by state provides the total fees per vehicle over its lifetime while the pie charts highlight the breakdown of the fees by source.



(a) Nissan Leaf (BEV 100 model)

(b) Toyota Prius (PHEV 10 model)

(c) Chevrolet Volt (PHEV 40 model)

Figure 3.7: Lifetime fees for EVs by state. The color-code by state provides the total fees per vehicle over its lifetime while the pie charts highlight the breakdown of the fees by source.

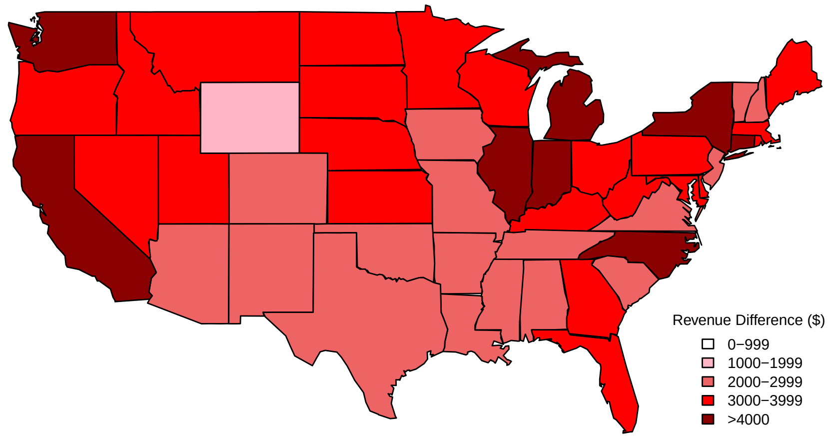
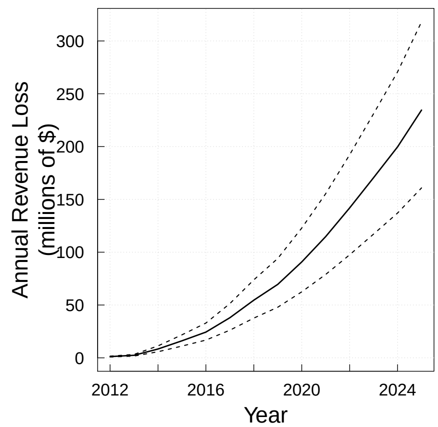


Figure 3.8: Difference in lifetime fees between Ford F-150 and Nissan Leaf by state as an upper bound estimate of revenue decrease at the margin.

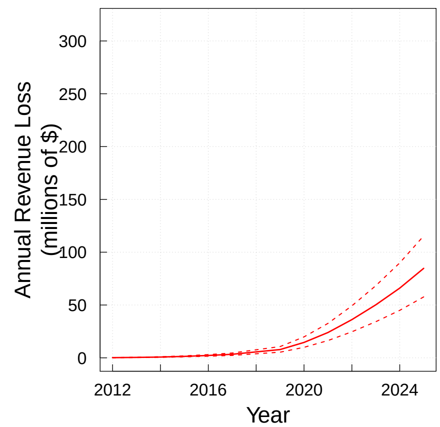
3.3.3 Assessing and projecting aggredated funding deficits

We estimate the annual loss in future revenue generation due to decreases in fuel tax collections from electric vehicles. Using projections from the EIA AEO 2013 for vehicle sales and proxying distributions of sales by state with the Toyota Prius, we roughly estimate annual decreases in total revenue generation (as described in Section 3.2.3). Assuming the sales trends provided in the EIA reference scenario hold, over the next decade revenue from use fees for electric vehicles will decrease by around $200 million annually.

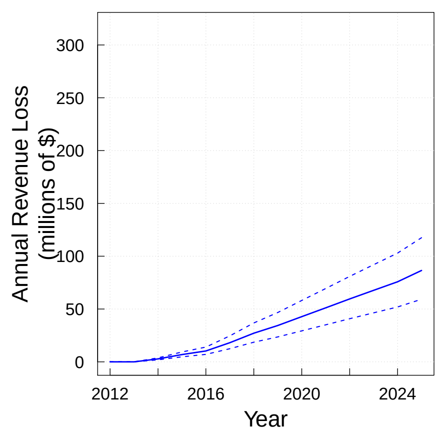
Similarly, we are able to estimate total revenue decreases by state due to EVs sold through 2025 (estimated using EIA 2013 AEO projections). The highest losses are a function of both the relative number of sales as well as each states' respective revenue-generation policies. While states with the highest populations expectedly have the greatest revenue loss, we are able to determine the magnitude of losses as affected by their level of EV adoption as seen in Figure 3.10. The high population states of California, Texas, Pennsylvania, and Florida all have total revenue decreases in excess of $70 million cumulatively from 2011 to 2025. Other



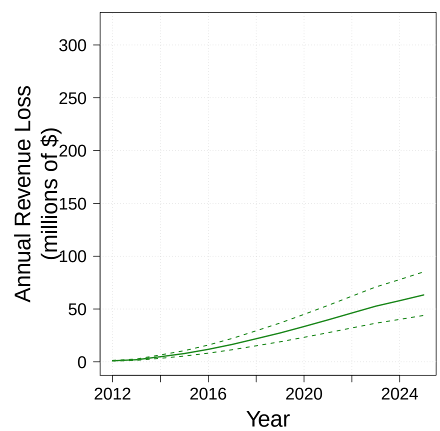
(a) Total Revenue Loss



(b) BEV Revenue Loss



(c) PHEV10 Revenue Loss



(d) PHEV40 Revenue Loss

Figure 3.9: Expected annual revenue loss for EVs with uncertainty from the distribution of sales by state. Assumption on sales by vehicle type come from EIA 2013

states with similar decreases include Wisconsin, Illinois, Virginia, North Carolina, and New York. We also normalize by population to see the effect of EV adoption per capita in Figure 3.11. The relative differences are similar with the exception of a few states such as Colorado and Texas, both of which have lower relative losses when normalized to population size.

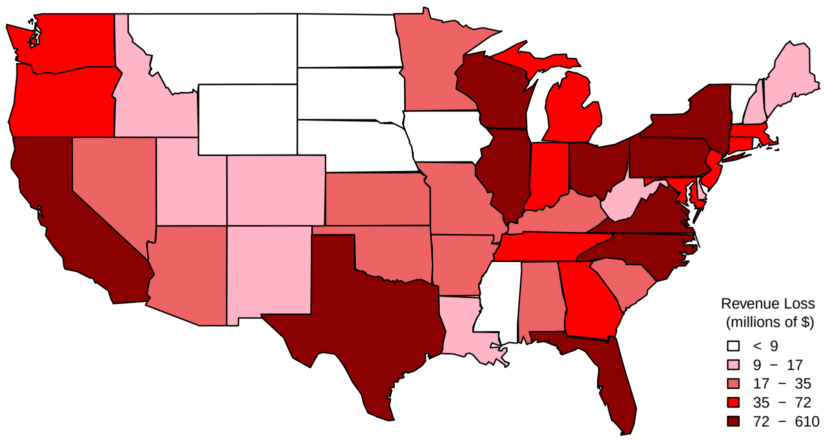


Figure 3.10: Expected cumulative revenue loss through 2025 for EVs by state.

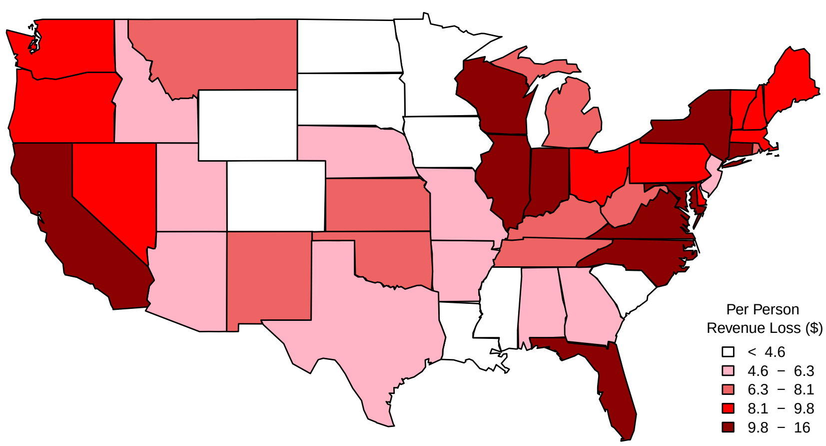
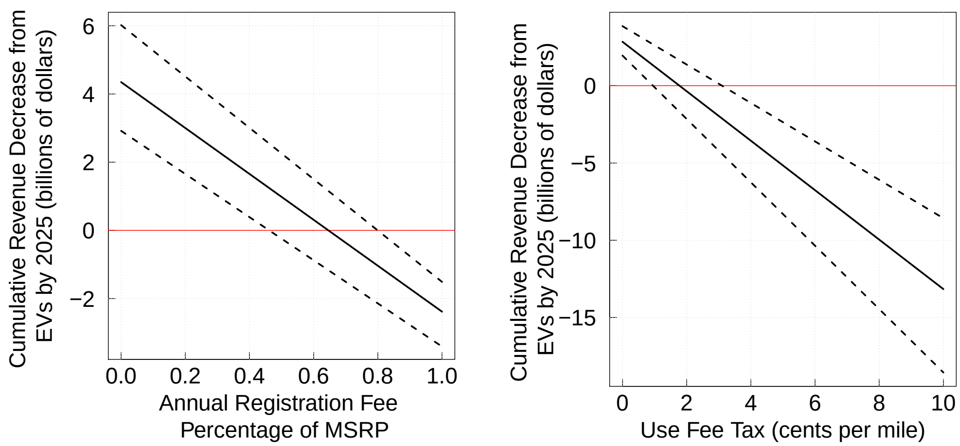


Figure 3.11: Expected cumulative revenue loss through 2025 for EVs by state, normalized to 2012 population.

3.3.4 Policy strategies to overcome the funding deficit arising from EV adoption

We demonstrate potential alternative strategies for revenue generation. An annual registration fee similar to Colorado or Wyoming wherein a fee is charged based on a percentage of the MSRP of the vehicle could be incorporated to make up the decrease in revenue generation from EVs. Figure 3.12 demonstrates a fee of approximately 0.6% would breakeven the cumulative annual revenue generation overtime and even small increases over this amount can yield large increases in revenue (on the order of $1-2 billion). Similarly, instead of a use fee by taxing gasoline, a use fee on the mileage driven by the vehicle would also suffice as a replacement. At approximately 2¢ per mile, revenue generation from EVs would breakeven in comparison to comparable ICV replacements.



(a) Registration Fee Analysis (b) Use Fee Analysis

Figure 3.12: Sensitivity Analysis on Alternative Revenue Generation Policies.

Alternatively, revenue neutrality can also be maintained by imposing a tax on electricity when charging an EV. The required fee would be approximately 4.5¢ when considering the efficiency of a Volt (35 kWh/100 miles). While this is a relatively small fee, we do not consider difficulties with policy implementation of this nature. Lastly, we also consider distribution of the revenue loss across all drivers in the US and roughly estimate that the total required tax would be a mere 0.02¢ per gallon of gas becase of the relatively small number of EVs that would be sold in comparison to the ICV fleet. We display a short summary of these fee increases on consumers in Table 3.2.

Table 3.2 demonstrates that for EV owners, bearing the cost of the fee increases can result in relatively large increases to their existing registration fees (or electricity bills). However, disaggregating the fees among the general population of drivers is a negligible increase in

Table 3.2: Absolute and relative increases in fees for two payee groups (depending on state)

	EV Owners		All vehicle owners	
Source	Absolute Increase	Relative Increase in Annual Bill	Absolute Increase	Relative Increase in Annual Bill
Annual registration fee	$200	60%-1400%	$1	0.5%-7%
Use fee	$0.045/kWh	100%-266%	$0.002/gal	0.05%

fees paid by drivers.

3.4 Conclusion

While the decrease in annual revenue generation of $200 million is a relatively small amount of total national revenue generation ($\sim$1%), the decrease represents part of a larger issue where expenditures have over taken revenue generation in the recent past. Future strategies to increase revenue generation should accomodate the increasing adoption of EVs in the market. While our analysis provides a monetary strategy to overcome the impact of EV adoption on revenue generation for transportation infrastructure, there are still two significant issues. Firstly, implementation of our proposed strategies has been traditionally difficult. Political backlash against increased fees could prevent such policies from being adopted despite the fact that the majority of vehicles (ICVs) would see no effective increase in fees. Moreover, a use fee tax by mileage could present a technically difficult challenge as odometer readings would be required. Secondly, increasing fees for EVs works in stark opposition to the incentivization of alternative fuel vehicles that both federal and state governments have made (e.g. tax credits). A targeted increase in fees for EVs would be an inefficient mechanism that may hinder the promotion of adoption strategies. Nevertheless, decreasing revenue generation from EVs represents a small but growing problem that should be considered in future strategies to increase revenue for transportation infrastructure funding.

Chapter 4

Alternative Fuel Vehicle Incentives in Corporate Average Fuel Economy Policy Increase Greenhouse Gas Emissions

4.1 Introduction

4.1.1 A History of CAFE

In response to the oil crisis of 1973 the United States passed the Energy and Policy Act of 1975[1], which included Corporate Average Fuel Economy standards. CAFE mandates that the average fuel efficiency of all new light-duty vehicles sold in a particular year must meet a specific target. These targets were initially the same for each manufacturer (though some manufacturers chose to pay fines rather than comply[2]) with separate targets for cars and light trucks. The first standards came into effect in 1978 for passenger cars and were

[1]Energy Policy and Conservation Act, 1975. Public Law. 94163. Congress.
[2]*Summary of CAFE Fines Collected.* National Highway Traffic Safety Administration. January 11, 2012.

soon followed by standards for light-duty trucks the following year. A full history of the standards and changes can be seen in Figure 4.1. The National Highway and Traffic Safety Administration (NHTSA) have traditionally regulated the standards but a recent court ruling in 2007 required the Environmental Protection Agency (EPA) to regulate CO_2 emissions as pollutants under the Clear Air Act[3]. As a result, the rule making for the newest set of CAFE standards and greenhouse gas (GHG) emissions standards were passed as a joint set of rules between NHTSA and EPA in 2012[4][5]. The EPA regulates the carbon emissions of the vehicles while NHTSA regulates the equivalent fuel efficiency of the vehicles.

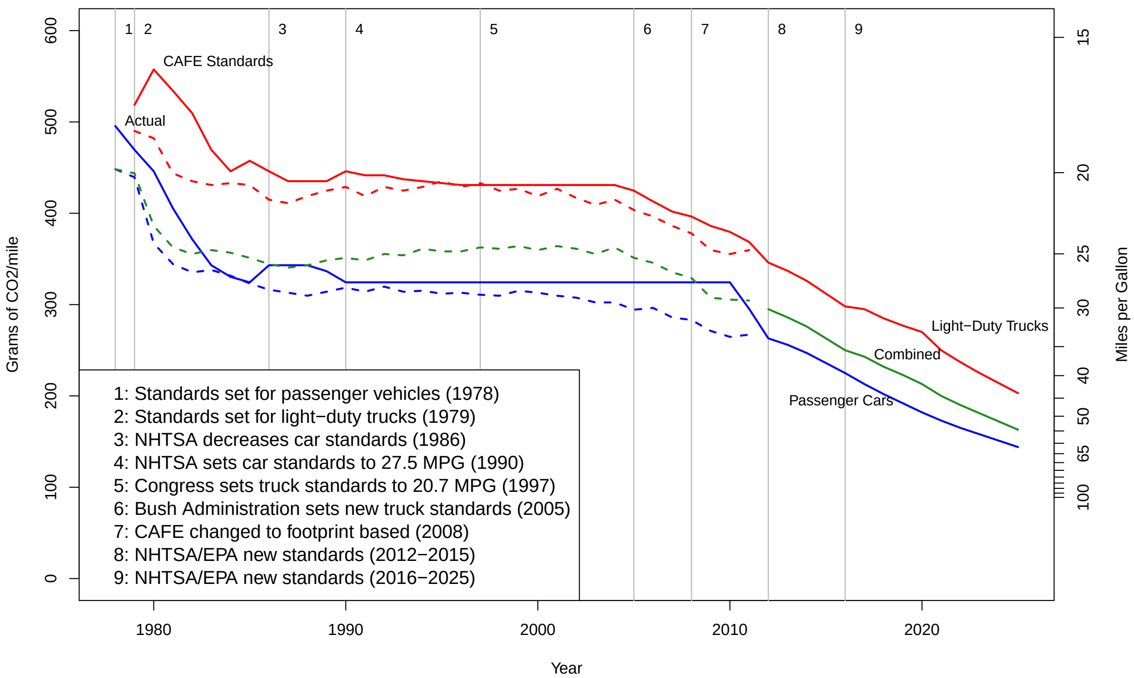


Figure 4.1: Historical CAFE Standards and Expected Joint Rulemaking Standard Requirements Through 2025[6][7]

[3] *Massachusetts v. Environmental Protection Agency*, 127 S. Ct. 1438, 549 U.S. 497, 167 L. Ed. 2d 248 (2007).

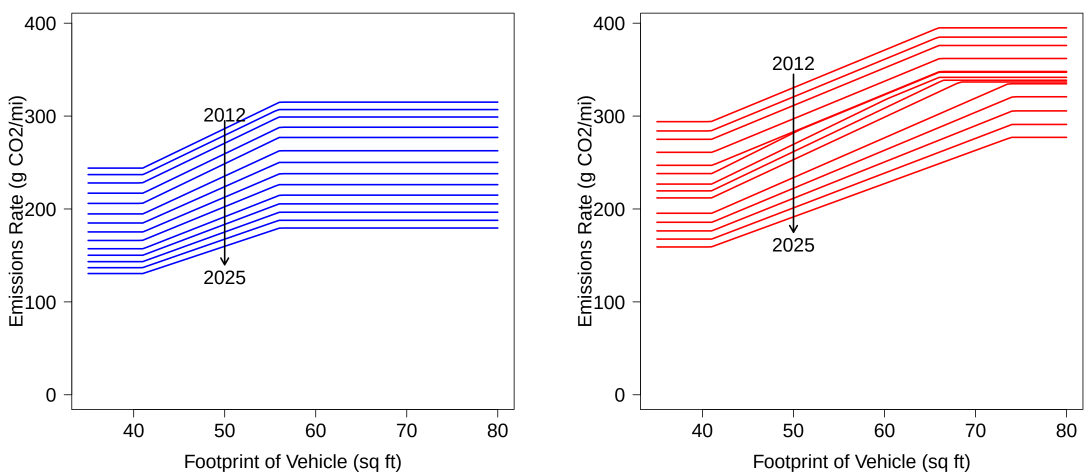
[4] Federal Register Vol. 75, No. 88: Light-Duty Vehicle Greenhouse Gas Emissions Standards and Corporate Average Fuel Economy Standards; Final Rule

[5] Federal Register Vol. 77, No. 199: 2017 and Later Model Year Light-Duty Vehicle Greenhouse Gas Emissions and Corporate Average Fuel Economy Standards

[7] Office of Transportation and Air Quality. *EPA and NHTSA Finalize Historic National Program to Reduce Greenhouse Gases and Improve Fuel Economy for Cars and Trucks*. EPA-420-F-10-014. April 2010

[7] Office of Transportation and Air Quality. *EPA and NHTSA Set Standards to Reduce Greenhouse Gases and Improve Fuel Economy for Model Years 2017-2025 Cars and Light Trucks*. EPA-420-F-12-051. August

In addition to the changes in the standards numbers, in 2008 the fuel efficiency standards were changed to an attribute-based standard. Specifically, the efficiency target for each vehicle is a function of its footprint: the product of vehicle wheelbase and track length - a measure of vehicle size. For both passenger cars and light-duty trucks, vehicles with larger footprint have less stringent efficiency targets. While each vehicle sold need not necessarily comply with the standard associated with its footprint, the sales-weighted average efficiency of all vehicles sold by each manufacturer must meet or exceed the sales-weighted standard defined by the footprints of the vehicles sold. Figure 4.2 summarizes the standard for cars and light-duty trucks as a function of vehicle footprint for years 2012 through 2025.



(a) Passenger car footprint based standards, 2012-2025

(b) Light-duty truck footprint based standards

Figure 4.2: Attribute-based CAFE standards[89]

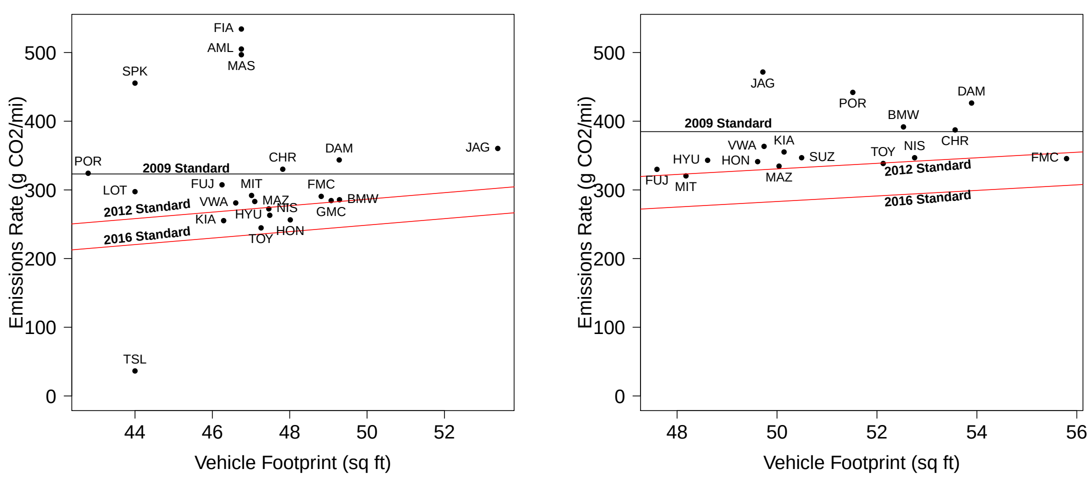
By 2025, the average fuel efficiency of new passenger cars and light-duty trucks will be required to meet or exceed 55 MPG. These requirements will likely have strong effects on the vehicle market, both for manufacturers, who must make significant technological improvements to keep pace with the mandate, as well as for consumers, who will have access to a different set of vehicle options at different prices. The policy will substantially decrease

2012

[9]Federal Register Vol. 75, No. 88: Light-Duty Vehicle Greenhouse Gas Emissions Standards and Corporate Average Fuel Economy Standards; Final Rule p. 25355-25357

[9]Federal Register Vol. 77, No. 199: 2017 and Later Model Year Light-Duty Vehicle Greenhouse Gas Emissions and Corporate Average Fuel Economy Standards p. 62782

gasoline consumption and corresponding GHG emissions per mile driven. Current compliance by manufacturers can be seen in Figure 4.3. For both cars and trucks the American manufacturers tend to be quite close to the standard, while Japanese manufacturers overcomply and European manufacturers undercomply and pay penalties[10]. However, as the standard increases in stringency and penalties for violation are increased, manufacturers will need to implement vehicle design changes and/or shift the portfolio of vehicles they sell. The only manufacturers whose 2009 passenger car fleet would have complied with the 2012 standard are Kia, Hyundai, Honda, and Toyota, and no manufacturers would have met the 2012 standard for light-duty vehicles.



(a) Compliance in 2009 for Passenger Cars (b) Compliance in 2009 for Light-Duty Trucks

Figure 4.3: Compliance of manufacturers[11] in 2009 with reference curves from Figure 4.2 representing future standards. While the majority of vehicle models lie in the linearly increasing portion of the standard curve, if manufacturers increase the footprints of their vehicles, the expected standards may not reflect the actual compliance requirement.

We aim to quantify the effect of CAFE AFV incentives. The Congressional Budget Office pointed out in a 2012 report: "With CAFE standards in place ... putting more electric (or other high-fuel-economy) vehicles on the road will produce little or no net reduction in total

[10] *Summary of CAFE Fines Collected*. National Highway Traffic Safety Administration. January 11, 2012. http://www.nhtsa.gov/staticfiles/rulemaking/pdf/cafe/CAFE_Fines-Jan2012.pdf

[11] AML=Aston Martin Lagonda, BMW=BMW, CHR=Chrysler, DAM=Daimler, FIA=Fiat, FMC=Ford Motor Company, FUJ=Subaru, GMC=General Motors Company, HON=Honda, HYU=Hyundai, JAG=Jaguar, KIA=Kia, LOT=Lotus, MAS=Maserati, MAZ=Mazda, MIT=Mitsubishi, NIS=Nissan, POR=Porsche, SPK=Spyker, TOY=Toyota, TSL=Tesla, VWA=Volkswagen

gasoline consumption and greenhouse gas emission" (Gecan et al.). This is because future stringent CAFE standards are expected to be binding with high penalties for violation, and under a binding standard the annual target would be achieved regardless of whether AFVs are sold. We investigate the influence of CAFE AFV incentives on this effect and find that increased sales of AFVs in place of conventional vehicles results in substantial emissions increases.

4.1.2 Literature Review

Our review of existing research on CAFE standards is divided into three sections: works that examine general impacts of CAFE on energy, economy, and the environment; research on the influence of CAFE on vehicle design decisions in the automotive industry; and studies on unintended policy effects from CAFE.

The CAFE program has had a profound impact on transportation in the United States: over the last several decades it has affected the emissions of hundreds of millions of vehicles and reduced consumption of gasoline on the order of billions of gallons. For this reason, understanding its effectiveness and efficiency as a policy to reduce emissions and oil consumption has been well studiedand hotly debated. In an earlier evaluation of CAFE standards, David Greene argues that fuel economy regulation has been economically efficient, and despite arguments of rebound effect has saved consumers $50 billion annually in comparison to 1975 levels of gasoline consumption. However, the author also warns that "simply because a corporate average fuel economy formula worked well in the past does not mean that a more efficient formulation does not exist" (Greene, 1998). Indeed, a number of critics argue that imposing gasoline taxes can more efficiently achieve the same outcomes as CAFE. Kleit finds that a long-term increase of 3 miles per gallon (MPG) in CAFE standards results in welfare losses of $4 billion annually, equivalent to a gasoline tax of $0.78 per gallon. Using an equilibrium model the author finds that a gas tax of $0.11 per gallon leads to the same gasoline savings as the CAFE standards while imposing only $290 million annually to consumers (Kleit, 2004). Similarly, Austin and Dinan use a Bertrand equilibrium model to project responses to fuel efficiency standards and find that gasoline taxes would result in around 60% lower welfare losses while achieving the same oil consumption decrease (Austin and Dinan, 2005). However, Gerard and Lave argue against critics that many externalities in the transportation sector can be addressed with sharp increases in gasoline fuel costs, but as a supplement to existing CAFE standards rather than eliminating the program entirely (Gerard and Lave, 2003). Given the contention over the usefulness of the policy, a careful understanding of its benefits and costs is crucial to properly evaluate CAFE.

A number of studies evaluating the policy have arisen in the last few years with the advent of the latest updates to the CAFE program. The EPA released a large report evaluating the new 2012 to 2016 standards, in addition to technical documentation describing their modeling efforts in devising the new standards, the report indicates that the fuel efficiency program is estimated to result in 1 billion metric tons of CO_2 reductions and savings of 1.8 billion barrels of oil. By 2050, the EPA expects reductions of 500 million metric tons of CO_2 annually as a result of transitioning to cleaner vehicles due to CAFE (epa, 2010). Since the announcement and implementation of the new standards, a wide variety of methods have been applied in order to estimate emissions savings and fuel reductions in an equilibrium framework (Karplus and Paltsev, 2012; Ross Morrow et al., 2010), LCA framework (Cheah et al., 2010), and through the use of decision theory (Bastani et al., 2012). Our study contributes to this body of work by identifying a specific policy mechanism that affects vehicle emissions but has been unaccounted for in previous research.

In addition to CAFE's effects on energy and the environment, fuel efficiency standards also affect automobile manufacturers' decision making for the design and choice of vehicles they sell. For example, Shiau et al. demonstrate in an oligopoly model that manufacturers make different vehicle design decisions (technologies improving vehicle fuel efficiency) depending on the stringency of the standards (Shiau et al., 2009). Whitefoot et al. show in their research that firms are likely to change vehicle design rather than strategic pricing in order to comply with standards, however firms are also incentivized to adjust prices to increase market share of light trucks due to higher profit margins (Whitefoot et al., 2011). More recently, Whitefoot and Skerlos reveal that as a result of the change to footprint based standards, firms have an incentive to increase vehicle size to comply with CAFE. This undermines fuel economy gains by 1-4 MPG and increases emissions from new vehicles by 5-15% (Whitefoot and Skerlos, 2012). The vehicle design response by firms, specifically vehicle fuel efficiency design, has implications on the emissions impact described in our work. In addition, vehicle footprint sizing can also have an effect on our modeling approach and its implications are discussed in the Appendix 8.3.1.

Finally, we consider works examining unintended consequences of CAFE regulation. Anderson and Sallee describe firms ability to exploit a bonus in fuel economy regulation compliance when automakers equip vehicles with flex-fuel capabilities. By equating the marginal cost of compliance (from the use of flex-fuel vehicles) to unobservable strategies, the authors are able to infer a one-MPG increase in standards cost between $9 and $27 per vehicle (Sallee, 2008). Our work examines the flex-fuel vehicle incentive, along with incentives for other alternative fuel vehicles, in the context of vehicle emissions. As mentioned previously, a Congressional Budget Office report indicates that the sale of electric vehicles does not improve fleet fuel efficiency because firms will ultimately converge to the CAFE standard (Gecan et al.). A paper by Goulder, Jacobsen, and Benthem delves more deeply into this issue, indicating that Pavley regulation (California alternative fuel vehicle sales mandate) in conjunction with CAFE standards are completely offset due to a leakage effect. This leakage essentially balances out high fuel efficiency sales in California and other Pavley states with lower fuel efficiency vehicle sales in other states, negating any net gains in efficiency (Goulder et al., 2012). Our work demonstrates that the effect is in fact negative net emissions rather than zero net emissions due to an unforeseen effect of the CAFE alternative fuel vehicle incentives.

The remainder of the work is organized as follows: Section 4.2 defines our method, data sources, and assumptions for changes in net emissions resulting from the sale of an AFV in place of a conventional vehicle. In Sections 4.3 and 4.4, we discuss the analysis, results, and implications.

4.2 Data & Methods

4.2.1 Calculating Standards Compliance with Alternative Fuel Vehicles

For illustration we present the case where the vehicles of interest have the same footprint, and we derive the more general case (where a vehicle with one footprint is replaced by a vehicle with another footprint as a result of the AFV incentives) in supplemental material. Central to our analysis is the assumption that manufacturers will comply with future standards without significantly exceeding them. We note that both the EPA[12] and the Congressional Budget Office[13] both make similar assessments in their analysis of the effects of the CAFE/GHG standards. The standards are calculated separately for each manufacturer each year. The basic relation is:

$$\frac{\sum_j n_j s_j}{N} = \frac{\sum_j n_j r_j}{N} \tag{4.1}$$

where n_j is the number of units of vehicle model j sold by the manufacturer in the focal year, s_j is the footprint-based standard associated with vehicle model j in the focal year, r_j is the GHG emission rate for vehicle model j, and $N = \sum_j n_j$. EPA policy requires that the

[12] "Under the EPA GHG program, there is no ability for a manufacturer to intentionally pay fines in lieu of meeting the standard...[the] EPAs analysis of benefits from its standard thus assumes full compliance". Federal Register Vol. 75, No. 88: Light-Duty Vehicle Greenhouse Gas Emissions Standards and Corporate Average Fuel Economy Standards; Final Rule. 25342-25343

[13] "Complying with rising CAFE standards is likely to be costly for automakers. Thus, manufacturers who intend to comply with the rules (rather than pay a fine) are likely to produce vehicles that just meet the standards without significantly exceeding them". Congressional Budget Office: Effects of Federal Tax Credits for the Purchase of Electric Vehicles. p. 14

sales-weighted average emission rate (right-hand side) be less than or equal to the standard (left-hand side), but because we assume the standard is binding, Equation (4.1) enforces equality.

CAFE policy provides two types of AFV incentives: weighting factors and multipliers. Weighting factors w reduce the effective emissions rate for AFVs used in CAFE calculations, allowing AFVs to count as though they have lower emissions than they actually do and effectively relaxing the standard. Multipliers m allow each AFV sold to count as more than one vehicle sold in CAFE calculations, increasing the denominator and effectively relaxing the standard further. The resulting relation for CAFE with AFV weights and multipliers is:

$$\frac{\sum_{j} n_j s_j}{N} = \frac{\sum_{j \in C} n_j r_j + \sum_{j \in A} \left(w_j p_j r_j^{\mathrm{A}} + (1 - p_j)\, r_j^{\mathrm{G}} \right) n_j}{\sum_{j \in C} n_j + \sum_{j \in A} n_j m_j} \tag{4.2}$$

where $w_j \in [0, 1]$ is the weighting factor for AFV model j, $m_j \geq 1$ is the multiplier for AFV model j, r_j^{A}, and r_j^{G} are the emission rates of AFV model j when operating on its alternative fuel and gasoline, respectively, and p_j is the assumed portion of AFV miles propelled using the alternative fuel ($p_j = 1$ for pure AFVs but $p \in [0, 1]$ for dual fuel vehicles that use a mix of gasoline and an alternative fuel, such as flex fuel vehicles and plug-in hybrid electric vehicles). Table 4.1 summarizes weights, multipliers, and assumed portion of VMT operating on the alternative fuel for each of the AFV types included in the 2012-2016 rules. These incentives are identical in both the EPA GHG standards and CAFE MPG standards[14].

The GHG rules for model years 2012-2016 offer different incentives for flex fuel vehicles (FFVs), compressed natural gas vehicles (CNG), battery electric vehicles (BEVs), plug-in

[14] Office of Transportation and Air Quality. EPA and NHTSA Set Standards to Reduce Greenhouse Gases and Improve Fuel Economy for Model Years 2017-2025 Cars and Light Trucks. EPA-420-F-12-051. August 2012 p. 9

[15] Section C: Additional Credit Opportunities for CO_2 Fleet Average Program, Subsection 2: Flexible Fuel and Alternative Fuel Vehicle Credits. Federal Register Vol. 75, No. 88

Table 4.1: Summary of AVI Provisions from 2012-2016[15]

Vehicle Type	Proportion Operating on Alternative Fuel	Multiplier	Weighting Factor
ICV	0	1	1
FFV	0.5	1	0.15
CNG	1	1	1
BEV	1	1	0
PHEV	0.29-0.66	1	0
FCV	1	1	0

hybrid electric vehicles (PHEVs), and fuel cell vehicles (FCVs). For FFVs, both passenger cars and light-duty trucks are assumed to operate 50% of the time gasoline and 50% of the time on ethanol, and the portion of PHEV travel propelled by electricity depends on the vehicle's all-electric range (computed by the EPA). There are no multipler gains in CAFE policy through 2016. The legislation assigns a weighting factor of 0.15 for FFVs but limits the overall gain from this effect to 1.2 miles per gallon average increase for each manufacturer from 2012 through 2014 with a limit to 1 mile per gallon increase in 2015, after which FFV weights expire. BEVs, FCVs, and PHEVs (while in electric mode) are treated as though they have no emissions for CAFE policy, despite known upstream emissions implications (Samaras and Meisterling, 2008; Michalek et al., 2011; Majeau-Bettez et al., 2011). For BEVs and FCVs, there is a cumulative production limit for AFV incentives of 200,000 vehicles unless a manufacturer sells at least 25,000 BEVs and FCVs, whereupon the cap is raised to 300,000 vehicles in 2012-2016.

Table 4.2 shows that during the 2017-2021 period, many alternative fuel vehicles are provided with both weighting factors and multipliers as a result of manufacturer concerns that they would be unable to meet the steep fuel efficiency requirements without the incentives. The multipliers for BEVs and FCVs are larger than the multipliers for PHEV and CNG vehicles because the EPA believes that GHG emissions reduction potential is higher for these two technologies[16]. After the initial increase in 2017, all multipliers are set to reduce over

[16]Subsection 3: Advanced Technology Vehicle Incentives for Electric Vehicles, Plug-in hybrids, and Fuel

time, reverting to 1 (no multiplier incentive) by 2022.

Table 4.2: Summary of AVI Provisions from 2017-2025[17]

Vehicle Type	Proportion Operating on Alternative Fuel	Multiplier (2017-2019)	Multiplier (2020)	Multiplier (2021)	Multiplier (2022-2025)	Weighting Factor
ICV	0	1	1	1	1	1
FFV	0.15	1	1	1	1	1
CNG	1	1.6	1.45	1.3	1	1
BEV	1	2.0	1.75	1.5	1	0
PHEV	0.29-0.66	1.6	1.45	1.3	1	0
FCV	1	2.0	1.75	1.5	1	0

Weighting factors are reset from the 2012-2016 period to the values seen above in Table 4.2 with a new set of sales caps. The cap for this period is a cumulative sale of 600,000 for the combination of BEVs and FCVs from 2022 through 2025 if they produced 300,000 in 2019-2021. Otherwise the cap is a cumulative 200,000 during that period for BEVs and FCVs. Our models do not explicitly include the sales cap limits since the caps are on a per manufacturer basis and not expected to be binding (only the largest volume manufacturers could meet the cap if they converted a substantial portion of their fleet to alternative fuel vehicles). FFV weighting factors expire in 2016 and the assumed proportion of FFV miles that are propelled by gasoline increases from 50% to 85% in 2017.

4.2.2 Increase in emissions from CAFE AFV Incentives

We examine a firm with J vehicle models and compute the effect of AFV sales with and without CAFE AFV incentives by treating the bulk of the fleet ($j = 3, 4, ..., J$) as being fixed at the CAFE standard ($\sum_{j=3}^{J} n_j s_j = \sum_{j=3}^{J} n_j r_j$) and focusing on two particular vehicles models in the fleet: an AFV ($j = 1$) and a conventional vehicle ($j = 2$) whose fuel efficiency is adjusted to balance the AFV effect and return the overall fleet average to the CAFE standard. Using the relationships described, we can compute the emissions rate of the

Cell Vehicles. Federal Register Vol. 77, No. 199 p. 62814

[17]Subsection 3: Advanced Technology Vehicle Incentives for Electric Vehicles, Plug-in hybrids, and Fuel Cell Vehicles. Federal Register Vol. 77, No. 199

balancing vehicle r_2 in the two cases:

Emissions rate for AFV balancing vehicle r_2 without CAFE AFV Incentives:

$$\frac{n_1 s_1 + n_2 s_2 + \sum_{j=3}^{J} n_j s_j}{N} = \frac{n_1 \left(p_1 r_1^{\mathrm{A}} + (1-p_1)\, r_1^{G}\right) + n_2 r_2 + \sum_{j=3}^{J} n_j r_j}{N} \tag{4.3}$$

$$\therefore r_2 = \frac{N\bar{s} - \sum_{j=3}^{J} n_j r_j - n_1 \left(s_1 - \left(p_1 r_1^{\mathrm{A}} + (1-p_1)\, r_1^{\mathrm{G}}\right)\right)}{n_2} \tag{4.4}$$

Emissions rate for AFV balancing vehicle r_2' with CAFE AFV Incentives:

$$\frac{n_1 s_1 + n_2 s_2 + \sum_{j=3}^{J} n_j s_j}{N} = \frac{n_1 \left(w_1 p_1 r_1^{\mathrm{A}} + (1-p_1)\, r_1^{\mathrm{G}}\right) + n_2 r_2' + \sum_{j=3}^{J} n_j r_j}{N + n_1 (m_1 - 1)} \tag{4.5}$$

$$\therefore r_2' = \frac{N\bar{s} - \sum_{j=3}^{J} n_j r_j - \bar{s} n_1 (m_1 - 1) + n_1 \left(s_1 - \left(w_1 p_1 r_1^{\mathrm{A}} + (1-p_1)\, r_1^{\mathrm{G}}\right)\right)}{n_2} \tag{4.6}$$

Increase in balancing vehicle emissions rate due to CAFE AFV incentives:

$$\Delta r_2 = r_2' - r_2 = \frac{\bar{s} n_1 (m_1 - 1) + n_1 (1 - w_1)\, p_1 r_1^{\mathrm{A}}}{n_2} \tag{4.7}$$

The increase in the balancing vehicles emissions rate due to the AFV incentives is a function of the emissions rate of the AFV when operating on its alternative fuel (r_1^{A}), the proportion of vehicle operation propelled by the alternative fuel (p_1), the multiplier (m_1), the weighting factors (w_1), and the sales volume of each (n_1 and n_2). When the multiplier is 1 and the weighting factor is 1, the AFV incentive effect is zero. For $m > 1$ or $w \in [0, 1)$, the effect of AFV incentives is to increase emissions.

4.2.3 Model Inputs

Table 4.3 summarizes emission rates for a set of US flex fuel and electric vehicles based on EPA Fuel Economy estimates using 5-cycle tests for measuring fuel efficiency. However, the standards set by NHTSA/EPA correspond to requirements based on 2-cycle tests. 5-cycle tests typically result in lower fuel efficiency numbers than 2-cycle tests, which means that the inputs for r^{A} and r^{G} will be higher (on an emissions rate basis) relative to the standard. As a result, our estimates for emissions will be slightly biased. Emissions associated with electricity consumption are also from EPA Fuel Economy estimates. We use their figures for national electric grid averages for simplification[18]. Use of average emissions rates are likely optimistic compared to the marginal emissions associated with charging EVs because marginal generation used to respond to new load tends to come from fossil fuel plants (Siler-Evans et al., 2012). However, average emission rates reflect figures described by the EPA and use of average rates avoids the need to make assumptions about dispatch, retirement, and capacity expansion. The actual emission values for regulation are currently unknown as the EPA currently consider EV emissions to be 0 grams of CO_2 per mile. Values for p are also determined from EPA Fuel Economy.

To compute lifetime emissions from each vehicle, we multiply the marginal vehicle emissions rate effect estimated in Equation (4.8) by vehicle miles travelled (VMT). We estimate VMT using data from the National Household Travel Survey (NHTS)[20]. Specifically, in each year our analysis uses annual average VMT for each vehicle type using draws from the set of all vehicles of the same age in the NHTS data. The lifetime of each vehicle is simulated using an exponential decay function, based on a report from the National Highway Traffic

[18] Electricity consumption based on EPA Emissions and Generation Resource Integrated Database (eGRID2012 Version 1.0) using the Power Profiler ZIP Code tool (Version 4.1)

[20] U.S. Department of Transportation, Federal Highway Administration, 2009 National Household Travel Survey. URL: http://nhts.ornl.gov.

Table 4.3: Summary of Vehicle Input Attributes[19]

Vehicle Make and Model	Vehicle Type	Gasoline Emissions Rate, r^{G} (grams CO_2/mile)	Alternative Fuel Emissions Rate, r^{A} (grams CO_2/mile)	Proportion of Operation on Alternative Fuel, p
Chevrolet Impala	FFV	319	379	0.50
Ford Focus	BEV	n/a	159	1
Nissan Leaf	BEV	n/a	144	1
Toyota Prius	PHEV	127	143	0.29
Chevrolet Volt	PHEV	177	171	0.66
Mitsubishi MiEV	BEV	n/a	148	1
Toyota RAV4	BEV	n/a	219	1

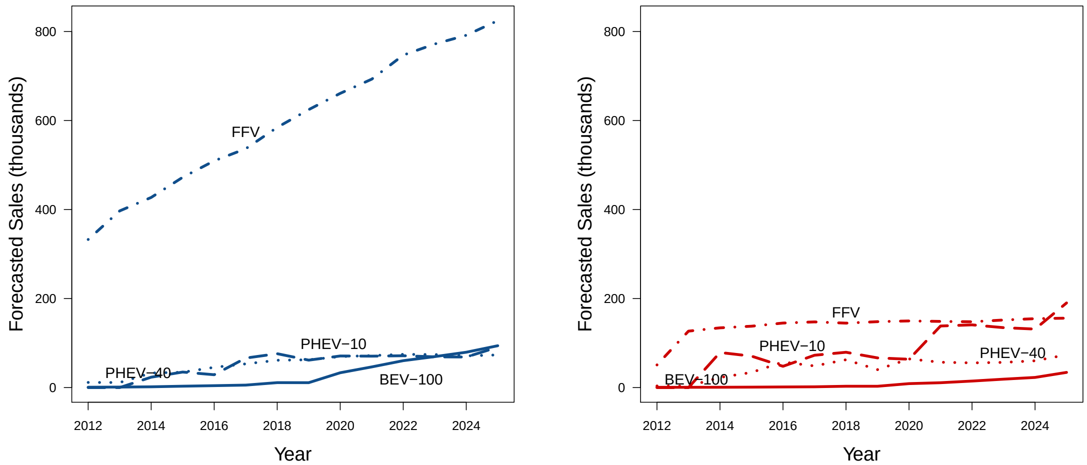
Safety Administration (Lu, 2007). We define γ_j as the lifetime greenhouse gas emissions released from vehicle model j, where v is the distance traveled by each driver as a function of the vehicle's lifetime l. We use a Monte Carlo simulation with $c = 10,000$ draws of vehicle lifetimes. The total increase in emissions due to the CAFE AFV incentives is the total increase caused by the balancing vehicle's increased emissions rate:

$$\Delta\gamma_2 = v\left(l_c\right) l_c \Delta r_2 \tag{4.8}$$

To estimate the net effect of CAFE AFV incentives on fleet use-phase emissions, we define the marginal vehicle effect by the number of vehicles (the n_1 in Equation (4.7)) using projections of AFV sales through 2025 from the Energy Information Agency (EIA)[21]. We compare results using EIA forecasts made in 2012 and forecasts made in 2013. The sales of AFVs, particularly FFVs, are substantially higher in the 2012 projections (at nearly 1 million sales annually) but have since been adjusted downwards in the 2013 projections.

As representative vehicles (for r^{A} and r^{G}) in each vehicle technology category of sales from the EIA AEO projections, we estimate our model using the Toyota Prius PHEV as the PHEV10, the Chevrolet Volt as the PHEV40, and the Nissan Leaf as the BEV100. For the

[21]U.S. Department of Energy/Energy Information Administration, *Annual Energy Review 2013*. DOE/EIA-0383(92). Washington, DC (2013)



(a) EIA projections made in 2012

(b) EIA projections made in 2013

Figure 4.4: Projections of alternative fuel vehicle sales through 2025 by the Energy Information Agency

representative FFVs r^{A} and r^{G}, we draw from historical sales weighted emissions rates of FFVs over the last decade (leading to greater uncertainty in aggregate FFV numbers).

4.3 Results & Discussion

Figure 4.5 illustrates how the inclusion of CAFE AFV incentives result in increased emission rates for the case of the Chevy Volt, given the annual CAFE GHG emissions standards (black line). Without AFV incentives the average of the Volt emissions rate (solid blue) and the balancing vehicle emissions rate (solid red) is equal to the standard in each year. With the AFV incentives, the adjusted emissions rate for the Volt used in CAFE accounting calculations is artificially lowered using weights (dotted blue), and the balancing vehicle (dotted red) has substantially higher emissions (with a peak in 2017 due to the implementation of multipliers). The net increase in average emissions rate resulting from the AFV incentives is the difference between the red lines (shaded area). For the Volt, this increase is about 100 to 250 g CO_2/mi, depending on the year. Across all of the AFVs listed in Table 4.3, the increase ranges between 50 to 400 g CO_2/mi comparable to the emissions that would have been created if an additional conventional light-duty vehicle were added to the fleet. Figure 4.6 summarizes the increase in emissions rate for these AFV models.

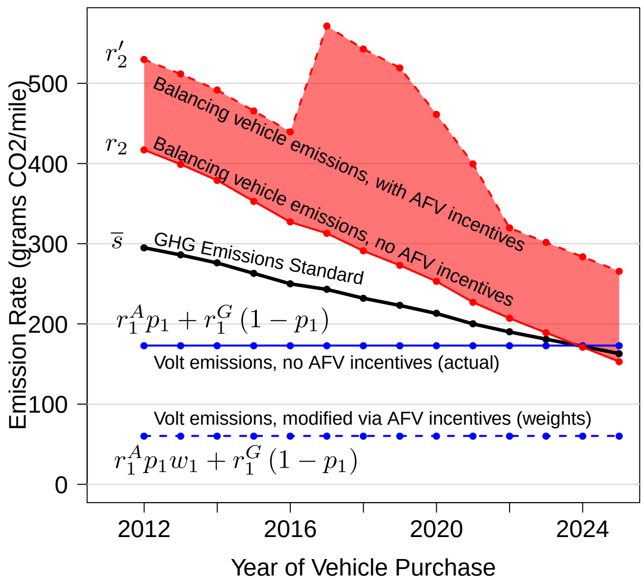


Figure 4.5: Relative emission rates for a Chevy Volt and Car 2 that balances to the CAFE Standards; with and without credits

Figure 4.6 shows that the greatest increase in emissions occurs for BEVs, such as the Nissan Leaf and the Ford Focus, because CAFE AFV incentives for these vehicles have weighting factors of 0, which increases balancing vehicle emissions by the BEV emission rate (see Equation (4.7)). Exacerbating this effect is the introduction of multiplier incentives in 2017 starting with a multiplier of 2.0, which further increases balancing vehicle emissions by an amount equal to the CAFE standard rate $\bar{s}$. The Chevrolet Volt and Toyota Prius follow a similar pattern but at lower emissions rates for the balancing vehicles. Flex fuel vehicles benefit from a 0.15 weighting factor, which expire in 2016. During the period of time when the weighting factor is active, the sale of such a flex fuel vehicle results in an increased balancing vehicle emission rate on the same order as the BEV effect per vehicle sold.

Figure 4.7 summarizes lifetime emissions over a range of potential realizations of vehi-

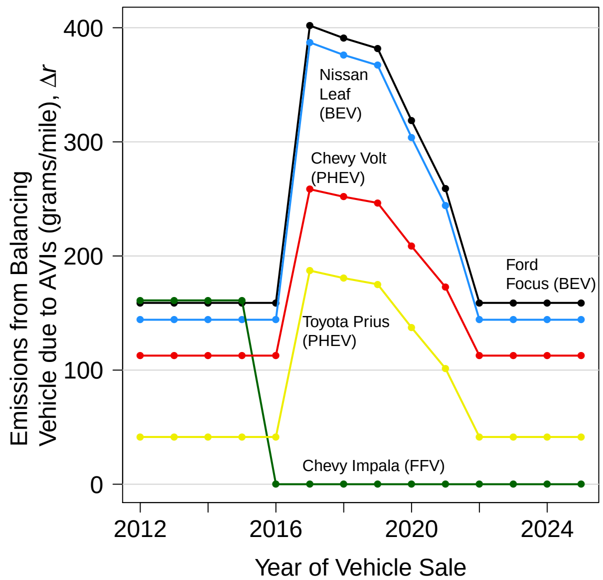


Figure 4.6: Incremental emission rate increase from Car 2 balancing to a range of AFVs

cle lifetime and VMT, using Monte Carlo simulation (see Section 4.2.3). The incremental emissions increase resulting from AFV incentives is 10 to 20 additional metric tons of CO_2 emitted during years where only the weighting factors are present and 20 to 50 additional metric tons CO_2 emitted during years where both multipliers and weighting factors are available. The PHEVs result in lower emissions than the BEVs because the increase in emissions is a function of the proportion of time spent in electric mode (see Equation (4.7)). The increases in emissions are comparable to those of a midsize vehicle, which can emit on the order of 30 to 40 tons of CO_2 over its lifetime.

We conduct a sensitivity analysis in Figure 4.8 over a range of weighting factors and multipliers. As determined in Equation (4.7), the relationship between the AFV incentives and the increase in emissions is linear. Over the range of proposed weights and multipliers from the NHTSA/EPA rulemaking, we find that the multipliers have the potential to lead to an increase in carbon emissions that is approximately twice as large as with the weighting factors. While the per vehicle emissions are uncertain given the variable nature of vehicle

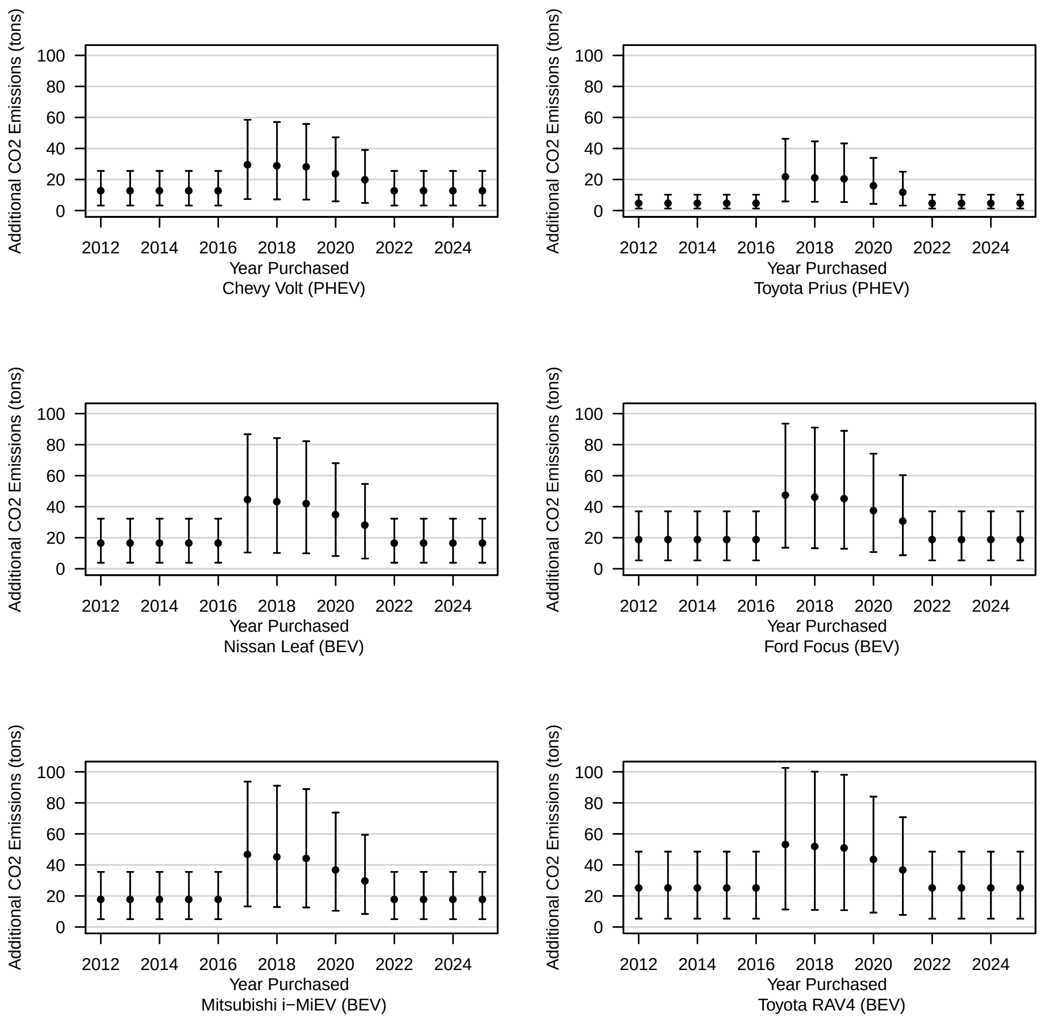


Figure 4.7: Additional emissions from a switch to an electric vehicle over the lifetime of the vehicle, 95% CI from variability in vehicle lifetime and driving behavior

lifetimes and annual miles driven, we find that on average at a weighting factor of 0 and a multiplier of 2 the incremental emissions balancing to Chevrolet Volt are about 15 and 30 tons of CO_2 respectively.

Using the EIA Annual Energy Outlook forecasts from 2012 and 2013, we are able to project our per vehicle emissions rate increases annually proxying the Toyota Prius PHEV for the PHEV10, the Chevrolet Volt for the PHEV40, the Nissan Leaf for the BEV100, and an assortment of vehicles to represent the FFVs. Figure 4.9 displays the cumulative increase

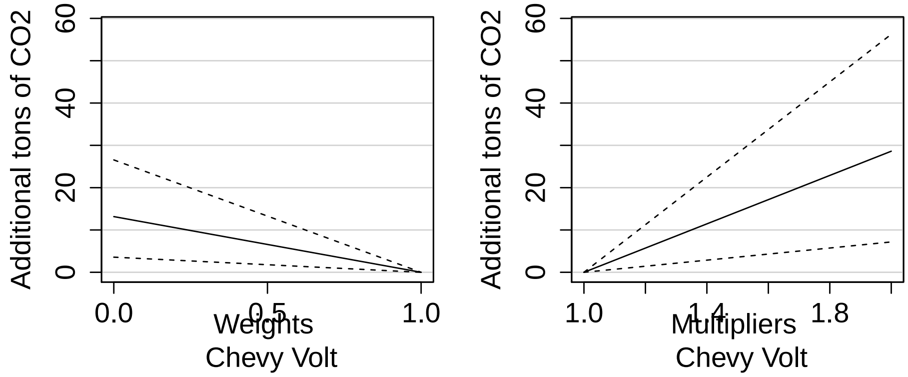


Figure 4.8: Sensitivity analysis of lifetime emissions when varying weight (fixed multiplier of 1) and multiplier (fixed weight of 1) when GHG emissions standard is set at 250 grams/mi, 95% CI from variability in vehicle lifetime and driving behavior

in CO_2 emissions resulting from AFV incentives for both 2012 and 2013 EIA projections. The largest relative difference between different vehicle technologies is the respective sales of each technology. The FFVs have the highest sales in both cases and as a result have the highest cumulative increase in emissions, though the emissions from FFVs peak earlier as their AFV incentives expire first.

Despite relatively large differences in projected sales, we find that the cumulative effect across all technologies ranges from 20 to 70 million tons of increase in CO_2 as seen in Figure 4.10. The large difference between the two cumulative increases is due to the radically different projections made by the EIA between 2012 and 2013 (see Figure 4.4).

4.4 Conclusion

We find that the presence of AFV incentives in the emissions standards will lead to an emissions increase of 50-400 grams of CO_2 per mile (depending on the vehicle) or 5 to 85 tons of CO_2 (depending on driving behavior and lifetime) for each AFV compared to the

[22]Images obtained from http://static.hgmsites.net/images/cache/2014-chevrolet-volt-5dr-hb-angular-front-exterior-view_100433516_400x240.jpg and http://carpaper.net/wp-content/uploads/2013/11/2012-kia-forte-5-door-5dr-hb-ex.jpg

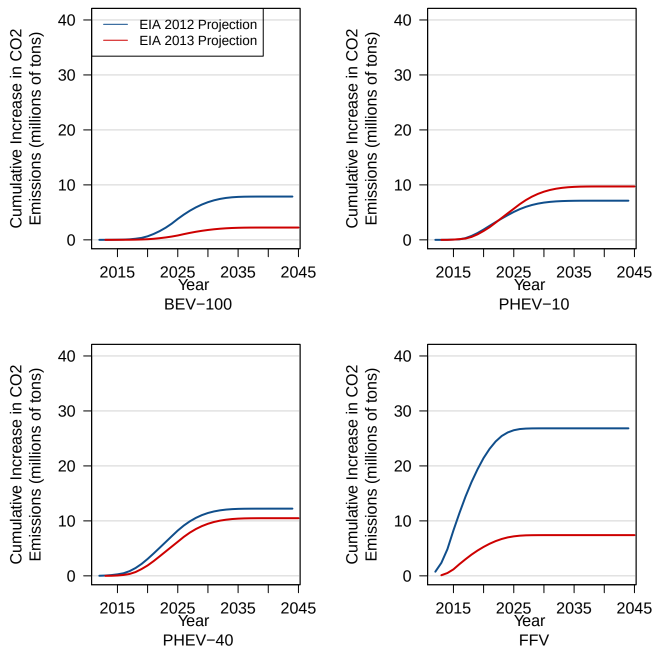


Figure 4.9: Increase in annual emissions due to incentive loopholes based on EIA 2012 and 2013 AEO Alternative Vehicle Sales Forecasts by vehicle technology

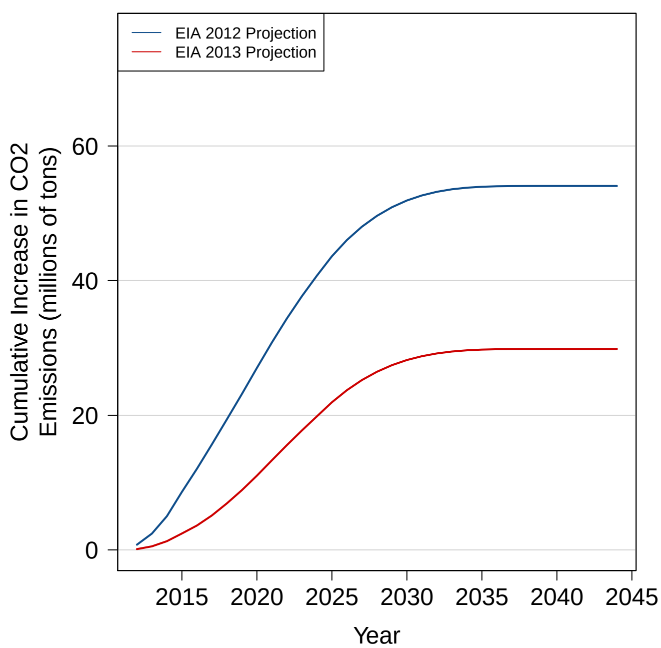


Figure 4.10: Total cumulative increase in annual emissions due to incentive loopholes based on EIA AEO Alternative Vehicle Sales Forecasts

Table 4.4: Emissions rate increase example by balancing a generic vehicle to a Chevrolet Volt in 2017[22]

	w/o Incentive	w/ Incentive
	173 g/mi	173 g/mi
	313 g/mi	571 g/mi

Total emissions rate increase: 258 g/mi

standards without AFV incentives. At the margin, we observe an effect such as that seen in Table 4.4. Using EIA projections from AEO, this will result in a cumulative increase of 20-70 million tons of CO_2. The AFV incentives in the CAFE and emissions standards are intended to incentivize market penetration of AFVs, which could provide a large benefit in the future. However, the AFV incentives come at a cost of at least 20-70 million additional tons of CO_2 being emitted relative to a case where the emissions standards exist without the AFV incentives. In total, this represents approximately 1-2% of the estimated emissions savings from the mandated standards. However, we caveat our results with the understanding that the emissions reductions from our results are relative to a baseline in which CAFE would exist with the same standards even in the absence of the incentives. In reality, the allowance of the incentives by EPA and NHTSA likely made manufacturers more amenable to the current stringent standards—without the alternative fuel incentives in place, it may be the case that the true counterfactual is a comparison to less stringent standards.

If the AFV incentives help to spur a large-scale adoption of AFVs that would not have happened otherwise, the long-term benefits would likely far outweigh the upfront emissions resulting from the implementation of AFV incentives. However, if the AFV incentives fail to incentivize the adoption of AFVs or the adoption of AFVs would still have occurred in the absence of AFV incentives, then the additional emissions would not be offset from later gains. Our analysis is not necessarily to denounce the inclusion of AFV incentives, but to estimate their short-term emission impacts. Efforts to implement AFV incentives should be asked to develop a persuasive argument that the expected long-term benefits will outweigh the near term costs.

Chapter 5

A Tale of Two Policies: How Fuel Economy Standards and Promotion of Alternative Vehicle Sales Can Increase Emissions

5.1 Introduction

In 1975, the United States began implementing policies in the form of minimum fuel efficiency standards for light-duty vehicles as a means of reducing energy consumption and enhancing the security of its fuel supply. Over time, several additional policies were implemented at the federal and state level. Our work focuses on recent changes to the Corporate Average Fuel Economy (CAFE) standards and in the California Air Resources Board (CARB) Zero Emissions Vehicle (ZEV) mandate. In particular, both programs recently sought to induce a larger adoption of alternative fuel vehicles (AFV), which will be the key focus of this work.

5.1.1 Corporate Average Fuel Economy Standards

The first set of CAFE standards was implemented within the Energy Policy Conservation Act of 1975[1]. Since their inception, the standards have been regulated by the National Highway and Traffic Safety Administration (NHTSA) at the Department of Transportation (DoT) and require manufacturers to meet specific sales-weighted average fuel efficiency for each model year, categorized by both passenger vehicles and light-duty trucks. The initial set of standards came into effect in 1978 for passenger cars and 1979 for light-duty trucks. Over time, the stringency of the standards was continuously increased, with the exception of 1986 when the Department of Transportation (DoT) loosened the standard. By 1990, the passenger vehicle standards were set at 27.5 miles per gallon (MPG). Seven years later, the light-duty truck standards were also increased to 20.7 MPG. In 2008, the standards were altered from a constant requirement to a footprint based standard[2] where cars with smaller footprints have higher fuel efficiency standards. In addition, due to a court ruling in 2007[3] that required the Environmental Protection Agency (EPA) to regulate carbon dioxide as a pollutant, the EPA jointly wrote the new set of standards with the NHTSA[45]. The standards in 2016 through 2025 are the newest set of mandates, with NHTSA regulating fuel efficiency (MPG) and EPA regulating carbon emission rates (grams of CO_2 per mile).

In an effort to increase the adoption of alternative fuel vehicles (AFV), the newest set of rules contains a provision concerning the sales of AFVs. The provision includes the

[1] Energy Policy and Conservation Act, 1975. Public Law. 94163. Congress.

[2] A vehicle footprint measures the area resulting from the product of the wheelbase and track length of the vehicle.

[3] *Massachusetts v. Environmental Protection Agency*, 127 S. Ct. 1438, 549 U.S. 497, 167 L. Ed. 2d 248 (2007).

[4] Federal Register Vol. 75, No. 88: Light-Duty Vehicle Greenhouse Gas Emissions Standards and Corporate Average Fuel Economy Standards; Final Rule

[5] Federal Register Vol. 77, No. 199: 201 and Later Model Year Light-Duty Vehicle Greenhouse Gas Emissions and Corporate Average Fuel Economy Standards

[7] Office of Transportation and Air Quality. *EPA and NHTSA Finalize Historic National Program to Reduce Greenhouse Gases and Improve Fuel Economy for Cars and Trucks*. EPA-420-F-10-014. April 2010

[7] Office of Transportation and Air Quality. *EPA and NHTSA Set Standards to Reduce Greenhouse Gases and Improve Fuel Economy for Model Years 2017-2025 Cars and Light Trucks*. EPA-420-F-12-051. August 2012

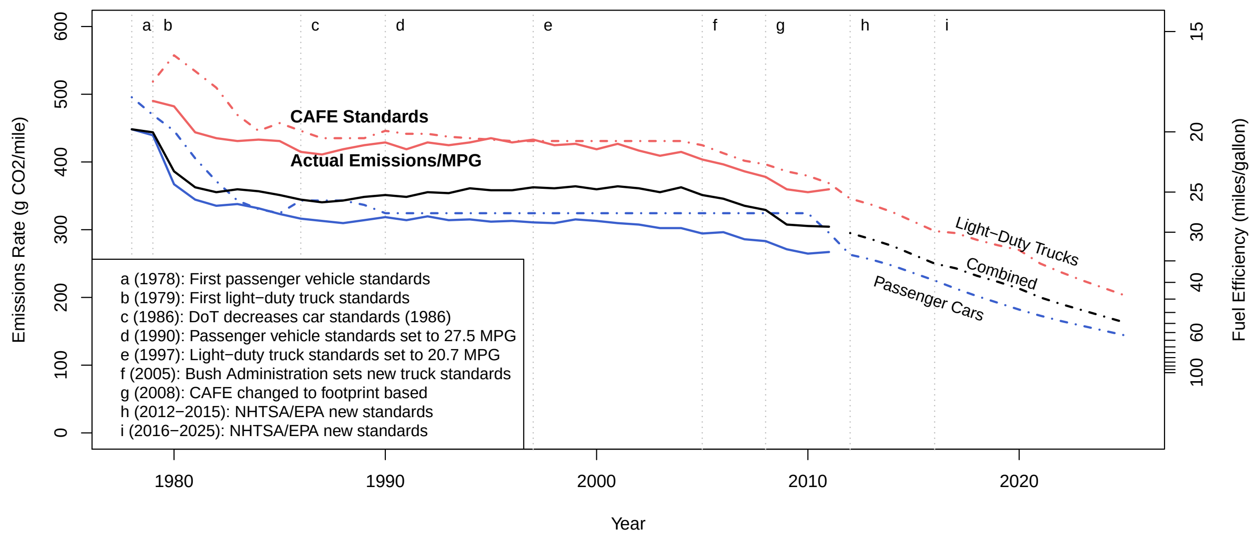


Figure 5.1: Historical and Expected CAFE Standards from 1978-2025[67]

establishment of AFV incentives for manufacturers consisting of multipliers and weighting factors. Manufacturers are required to achieve a certain level of MPG and CO_2 emissions per mile across all vehicles they sell, however the incentives artificially make the standards easier to achieve. A multiplier increases the count of a vehicle sale, e.g. a vehicle with a multiplier equal to two counts as two vehicles sold. A weighting factor proportionally decreases the emissions rate of a vehicle when it operates on an alternative fuel, e.g. a battery electric vehicle (BEV) with a weighting factor of 0.5 counts as having an emissions rate equal to half that of its actual rated emissions. A full list of AFV incentives can be found in Table 5.1 and Table 5.2. The proportion of time spent operating with alternative fuels are determined by the EPA, and we use these numbers to maintain consistency with the compliance calculations for fuel efficiency/emissions rates.

In addition to the information displayed in Table 5.1 and Table 5.2, we highlight several other aspects of the incentives. For FFVs, the weighting factor expires at the end of 2014 and cannot exceed 1.2 MPG average increase per manufacturer. Similarly, from 2012 through 2016 BEVs and FCVs have a cumulative production cap limit of 200,000 vehicles unless

[8]Section C: Additional Credit Opportunities for CO_2 Fleet Average Program, Subsection 2: Flexible Fuel and Alternative Fuel Vehicle Credits. Federal Register Vol. 75, No. 88

Table 5.1: Summary of AVI Provisions from 2012-2016[8]

Vehicle Type	Proportion Operating on Alternative Fuel	Multiplier	Weighting Factor
ICV	0	1.0	1.0
FFV	0.5	1.0	0.15
CNG	1.0	1.0	1.0
BEV	1.0	1.0	0
PHEV	0.29-0.66	1.0	0
FCV	1.0	1.0	0

25,000 vehicles of a technology are sold in 2012, which raises the cumulative cap to 300,000 vehicles.

Table 5.2: Summary of AVI Provisions from 2017-2025[9]

Vehicle Type	Proportion Operating on Alternative Fuel	Multiplier (2017-2019)	Multiplier (2020)	Multiplier (2021)	Multiplier (2022-2025)	Weighting Factor
ICV	0	1.0	1.0	1.0	1.0	1.0
FFV	0.15	1.0	1.0	1.0	1.0	1.0
CNG	1.0	1.6	1.45	1.3	1.0	1.0
BEV	1.0	2.0	1.75	1.5	1.0	0
PHEV	0.29-0.66	1.6	1.45	1.3	1.0	0
FCV	1.0	2.0	1.75	1.5	1.0	0

Similarly to the 2012 to 2016 provisions, there is a sales cap for AFV incentives of 200,000 BEVs, FCVs, and PHEVs in 2022 through 2025 unless there are cumulative sales of 300,000 BEVs, FCVs, and PHEVs in 2019 through 2021 whereupon the sales cap is raised to 300,000 in the latter half of the standards program.

5.1.2 Zero Emissions Vehicle Program

The ZEV requirements were originally established within Californias Low-Emission Vehicle (LEV) regulation by CARB. The ZEV program is meant to radically change the technology composition of the existing vehicle fleet. Its goal is to reduce emissions to 1990 levels by 2020

[9]Subsection 3: Advanced Technology Vehicle Incentives for Electric Vehicles, Plug-in hybrids, and Fuel Cell Vehicles. Federal Register Vol. 77, No. 199

in the face of increasing vehicle usage (as a result of AB 32[10] and AB 1493[11]). This is followed by an ambitious goal to reduce emissions to 80% of 1990 levels by 2050. In order to achieve this goal, CARB has set a stringent set of requirements for manufacturers to sell a certain number of alternative fuel vehicles every year. Table 5.3 gives a list of requirements for ZEV sales as a percentage of total sales in California. The 1990 and 1996 plans were both changed before taking effect in 1998 and 2003 respectively. The 2001 plan faced litigation[12] in state level lawsuits for linking ZEV credits to fuel efficiency metrics, during which an injunction was issued that prevented CARB from enforcing ZEV mandates in 2003 and 2004.

Table 5.3: Early California Air Resources Board Zero Emission Vehicles Program[13][14]

Year	1998-2000	2001	2003	2005-2008	2009-2011	2012-2014	2015-2017	2018+
1990 Plan	2%	5%	10%	-	-	-	-	-
1996 Plan	-	-	10%	-	-	-	-	-
2001 Plan	-	-	10%	10%	11%	12%	14%	16%

CARB amended the ZEV requirements in 2003, requiring manufacturers to sell 2% pure ZEVs (BEVs or FCVs), 2% advanced technology partial-ZEVs (AT-PZEVs, includes PHEVs and HEVs), and 6% partial ZEVs (PZEVs, fuel efficient ICVs) starting in 2005. However, manufacturers were given an alternative path of compliance, allowing AT-PZEVs to meet the ZEV requirements as long as they sold 250 FCVs through 2008 and 2,500 FCVs in 2009 through 2011. In addition, only manufacturers selling more than 60,000 vehicles annually in the state of California category are Ford, GM, Honda, Nissan, and Toyota[15]. The alternative

[10] Assem. Bill 32, 2005-2006 Reg. Sess. (Cal. 2006) www.leginfo.ca.gov/pub/05-06/bill/asm/ab_0001-0050/ab_32_bill_20060927_chaptered.pdf

[11] Assem. Bill 1493, 2002-2003 Reg. Sess. (Cal. 2002). www.arb.ca.gov/cc/ccms/documents/ab1493.pdf

[12] *Central Valley Chrysler-Plymouth, Inc., et al. v. Witherspoon*, Case No. CIV F-02-05017 REC SMS (E.D. Cal.); textitLiberty Motors, Inc., et al. v. California Air Resources Board, et al., Case No. 02 CE CG 00039 (Superior Court for Fresno County); textitDaimler Chrysler Corp. et al. v. California Air Resources Board et al., Case No. 02 CE CG 04456 HAC (Superior Court for Fresno County).

[14] Energy Information Administration: California Low Emission Vehicle Program and Carbon Standard for Light-Duty Vehicles, http://www.eia.gov/oiaf/archive/aeo04/leg_reg3.html

[14] Note that the requirements from Table 5.3 can be met with a large subcategory of vehicles as described in the main text

[15] California Environmental Protection Agency, Air Resources Board: Fact Sheet. http://www.arb.ca.gov/msprog/factsheets/2003zevchanges.pdf

compliance path has allowed manufacturers to meet the ZEV requirements without a drastic change in their sales. The current iteration of ZEV is their 2009 plan requiring sales of four vehicle categories: ZEV (FCVs and BEVs), transitional partial-ZEV (TZEV: PHEVs and dual-fuel FCVs), AT-PZEV (HEV, CNGV, and methanol FCVs), and PZEV (extremely clean conventional vehicles). The requirements schedule for the latest period can be found in Table 5.4.

Table 5.4: CARB ZEV requirements, 2012-2017 by percentage of total sales[16]

	2012-2014		2015-2017	
Vehicle Category	Compliance %	Credits	Compliance %	Credits
PZEV	6%	.2	6%	0
AT PZEV	3%	" + AC + LFC	2%	0
TZEV	2.21%	(" + ZVMT)*EIM	3%	0
ZEV	0.79%	2-7	3%	2-3

AC - Advanced Components Allowance
LFC - Low Fuel Cycle Allowance
ZVMT - Zero Emissions VMT
EIM - Early Intro Multiplier

Due to California's air quality standards preceding the federal Clean Air Act (CAA) of 1970, it retained authority to regulate its own emissions but allowed other states to adopt its standards under Section 177 of the CAA. Several other states that adopted Californias ambient air quality standards also elected to regulate sales of their vehicles under the ZEV policy. These states include Connecticut, Maryland, Massachusetts, New York, Rhode Island, Vermont, and Oregon.

5.1.3 Other Alternative Fuel Vehicle Policies

There are a number of other policies both regulatory and incentive based that help promote the adoption of alternative fuel vehicles. For example, both the Renewable Fuel Standards (RFS) and the Low Carbon Fuel Standards (LCFS) aim to lower the total carbon intensity

[16]California Environmental Protection Agency, Air Resources Board. *Staff Report: Initial Statement of Reasons, Advanced Clean Cars. 2012 Proposed Amendments to the California Zero Emission Vehicle Program Regulations.* December 7, 2011

of transportation fuels by promoting alternative fuels such as ethanol, compressed natural gas, and electricity. Additionally, there are various federal, state, and local incentives for alternative fuel vehicles. These incentives can be either monetary (tax credits or rebates such as the Plug-In Electric Drive Vehicle Credit IRC 30D) or non-monetary (e.g. free access to carpool lanes in California). We demonstrate in our work that the interaction of these policies with CAFE AFV incentives can lead to unintended increases in carbon emissions.

5.1.4 Literature Review

Our literature review focuses on several aspects of vehicle transportation policy: its effects on the adoption of alternative fuel vehicles as well as GHG emissions reductions, and an examination of unintended consequences of policy implementation.

A number of studies have measured the benefits of policies such as CAFE or ZEV. In 2010 and 2012, the EPA released reports evaluating the 2012-2016 and 2017-2025 CAFE standards. In their analysis, the EPA find that the fuel efficiency standards are expected to reduce CO_2 emissions by 960 million metric tons in 2012 to 2016 (epa, 2010). The effect we describe in this work is not accounted for in the EPA report and the emissions savings are an overestimate: the emissions increase in our study is a reduction from these overall emissions savings. Emissions savings from CAFE have been estimated in a number of other papers using a variety of methods: Ross Morrow et al. (2010) uses an equilibrium framework and estimates reductions to approximately 5% below 2005 emissions levels, on the order of several billion metric tons of CO_2. Karplus and Paltsev (2012) also estimate reductions in a general equilibrium model that result in 190 million metric tons of CO_2 annually, netting a cumulative savings of nearly 3 billion metric tons of CO_2 from 2012 through 2025.

Promoting the sales of alternative fuel vehicles does not contribute to the savings seen in the aforementioned literature. As described in a report from the Congressional Budget Office: "With CAFE standards in placeputting more electric (or other high-fuel economy) vehicles on the road will produce little or no net reduction in total gasoline consumption and greenhouse gas emissions" (Gecan et al.). In a study by Goulder et al. (2012) this effect is discussed in much more detail, specifically in relation to the Pavley limits, a set of GHG requirements in 14 US states. Despite the fact that Pavley standards are stricter than CAFE standards, the benefits from the policy is lost due to a leakage effect in which manufacturers comply with the policy where it is mandated but in non-Pavley states can sell larger and less fuel efficient vehicles. Our work demonstrates that the presence of two such policies is not net-zero emissions, but net-negative emissions in the short-term. In addition, costs are amplified as other policies such as ZEV incentive alternative fuel vehicle adoption.

We note that our work is strictly a measurement of the short-term emissions cost of vehicle policy interactions. In a study by Greene et al. (2013), the authors point out the importance of the ZEV mandates in helping to assist a transition towards vehicle electrification in the US passenger fleet. In certain scenarios, the long-term emissions benefits can outweigh the short-term losses. Our work is to ensure that the short-term costs are properly accounted for in future evaluations, as well as to point out inefficiencies and unintended effects from the policies.

Several studies have observed different unintended consequences from CAFE policy. For example, the Department of Transportation released a report in 2002 evaluating the Alternative Motor Fuels Act (AMFA) (part of CAFE Incentives Policy). The AMFA credit program provided credits to manufacturers for the sale of dual-fuel vehicles, which led to a large-scale adoption of FFVs of 1.2 million vehicles in only three years. Unfortunately, the report indicates that environmental benefits were "uncertain" due to the lack of availability of fuel and infrastructure for FFVs despite their ability to use ethanol fuel blends (dot, 2002). Anderson and Sallee (2011) take advantage of the fact that the FFV credits allow for easier compliance with the standards and are able to measure the marginal costs to automakers ($9-27$ per vehicle) for a one MPG increase in the standards. Whitefoot and Skerlos (2012) discuss another possible unintended consequence of the updated CAFE regulation, specifically the shift to a footprint-based standard. The authors describe how firms have an incentive to increase vehicle size rather than improving fuel efficiency to comply with CAFE, undermining fuel efficiency gains by 1-4 MPG. Lastly, Jenn et al. (2014) describe how AFV incentives in CAFE result in increased emissions as the sale of a marginal AFV allows manufacturers to balance their average fuel efficiency below their required standard. Our work is an extension of Jenn's work, and we describe how this effect is compounded by policies such as ZEV that promote the adoption of AFVs.

The remainder of the chapter is organized as follows: Section 5.2 defines derives an analytical expression for changes in net emissions resulting from various policy scenarios as well as our model input assumption. In Sections 5.3 and 5.4, we discuss the analysis, results, and implications.

5.2 Data & Methods

Our work examines four different policy scenarios:

Table 5.5: Policy Scenarios

Scenario	CAFE standards	CAFE AFV incentives	ZEV mandate
Pure CAFE (a)	✓	✗	✗
CAFE + ZEV (b)	✓	✗	✓
CAFE + AFVI (c)	✓	✓	✗
CAFE + ZEV + AFVI (d)	✓	✓	✓

In Section 5.2.1 we describe the mathematical formulation used to claculate emissions in each of the policy scenarios and in 5.2.2, we discuss the model input assumptions used to estimate the emissions increases found in our results.

5.2.1 Calculating total vehicle emissions

Scenario a Total Emissions

Scenario a is our baseline scenario with only CAFE standards. In any given year, we represent the required emissions rate [g CO_2/mi] compliance for an individual manufacturer as $\bar{s}$ and total of number of vehicles sold as N. While the CAFE standard applies individually to every manufacturer, our calculations are based for the entire vehicle fleet since we assume all manufacturers comply with the same expected standard (Figure 5.1). The cumulative emissions for scenario a, γ^a [g CO_2], is represented in Equation (5.1) where v [mi/yr] represents the average vehicle miles travelled per year and l [yr] represents the average vehicle lifetime. In addition to the use-phase emissions, we also include the incremental life-cycle analysis (LCA) emissions μ [g CO_2] from the production-phase of alternative fuel vehicles where n represents the number of vehicles sold of alternative fuel vehicle model j.

$$\gamma^a = \bar{s}Nvl + \sum_{j \in A} n_j \mu_j \tag{5.1}$$

The actual emissions rate of individual vehicles is irrelevant in this scenario as we assume that all manufacturers will comply with the standards exactly, hence total emissions can be represented as the product of the number of vehicles sold and the average emissions rates of all vehicles.

Scenario b Total Emissions

Scenario b includes both CAFE standards and ZEV mandates. The determination of the use-phase emissions is identical to Equation (5.1) as the CAFE standards are complied with exactly. However, production-phase emissions increases due to an increase in alternative fuel vehicle sales, we explicitly represent this increase as n^{ZEV} for every AFV model $j \in A$. Note that we assume the total number of vehicles N sold in each policy scenario remains constant, changes in sales of one vehicle model are assumed to be exactly matched by shift in the sales of another vehicle model (or distributed across the sales of several vehicle models).

$$\gamma^b = \bar{s}Nvl + \sum_{j \in A} n'_j \mu_j, \text{ where } n'_j = n_j + n_j^{ZEV} \tag{5.2}$$

Scenario c Total Emissions

In scenario c, the calculations become a function of the number of AFVs sold as the accounting in the CAFE standards for AFVs differs from traditional ICVs. Equation (5.3) represents the requirements to balance sales to the compliance standard, s [g CO_2/mi], for every vehicle model based on its footprint. On the left-hand side of Equation (5.3), AFV models $j \in A$ are balanced to the required standard by a group of traditional ICVs $j \in C_b$. The remainder of the vehicle models, $j \in C_a$, are assumed to comply with the overall standard $\bar{s}$. On the right-hand side of Equation (5.3), the actual emissions rates are represented as r [g CO_2/mi]. For dual-fuel vehicles, the emissions rates are determined by the proportion of time spent on alternative fuel p, its emission rate using traditional gasoline r^{G}, and its emissions rate using alternative fuels r^{A}. In addition, r^{A} is modified by a weighting factor w and the total sales N is modified bya multiplier value m (see Section 5.1.1).

$$\frac{\sum_{j \in A} n_j s_j + \sum_{j \in C_b} n_j s_j + \sum_{j \in C_a} n_j s_k}{N} = \frac{\sum_{j \in A} n_j \left(w_j p_j r_j^{\mathrm{A}} + (1 - p_j)\, r_j^{\mathrm{G}} \right) + \sum_{j \in C_b} n_j r_j + \sum_{j \in C_a} n_j r_j}{N + \sum_{j \in A} n_j \left(m_j - 1 \right)} \tag{5.3}$$

where $\dfrac{\sum_{j \in A} n_j s_j + \sum_{j \in C_b} n_j s_j + \sum_{j \in C_a} n_j s_j}{N} = \bar{s}$ and $\dfrac{\sum_{j \in C_b} n_j r_j}{\sum_{j \in C_b} n_j} = \bar{r}_j$, solving for the average emissions rate of the vehicles that balance the AFVs to the CAFE standard, $\bar{r}_j$, yields:

$$\bar{r}_j = \frac{\sum_{j \in A} \left(\bar{s}\left(N + n_j\left(m_j - 1\right)\right) - n_j\left(w_j p_j r_j^{\mathrm{A}} + \left(1 - p_j\right) r_j^{\mathrm{G}}\right)\right) - \sum_{j \in C_a} n_j r_j}{\sum_{j \in C_b} n_j} \tag{5.4}$$

The calculation for the cumulative lifetime emissions under scenario c, γ^c [g CO_2], is the

$$\begin{aligned} \gamma^c &= \left(\sum_{j \in C} n_j r_j\right) vl + \sum_{j \in A} n_j \mu_j \\ &= \left(\sum_{j \in A} n_j\left(p_j r_j^{\mathrm{A}} + \left(1 - p_j\right) r_j^{\mathrm{G}}\right) + \sum_{j \in C_b} n_j r_j + \sum_{j \in C_a} n_j r_j\right) vl + \sum_{j \in A} n_j \mu_j \end{aligned} \tag{5.5}$$

Substituting Equation (5.4) into Equation (5.5) and simplifying yields the calculation for total emissions in scenario c as seen in Equation (5.6). In addition to the emissions from the $\bar{s}N$ seen in Equations (5.1) and (5.2), we observe additional lifetime use-phase emissions as a function of the number of AFVs sold n_i and their corresponding weights w and multipliers m.

$$\therefore \gamma^c = \left(\left(\sum_{j \in A} n_j\left(p_j r_j^{\mathrm{A}}\left(1 - w_j\right) + \bar{s}\left(m_j - 1\right)\right)\right) + \bar{s}N\right) vl + \sum_{j \in A} n_j \mu_j \tag{5.6}$$

Scenario d Total Emissions

The model for cumulative emissions in scenario d is identical to scenario c with an increased number of AFV sales due to the ZEV mandates that increases quantities of AFV models n_i

and balancing models n_j while decreasing the quantities of traditional ICV models n_k.

$$\frac{\displaystyle\sum_{j\in A} n'_j s_j + \sum_{j\in C_b} n'_j s_j + \sum_{j\in C_a} n'_j s_j}{N} = \frac{\displaystyle\sum_{j\in A} \left(n'_j\right)\left(w_j p_j r_j^{\mathrm{A}} + \left(1-p_j\right) r_j^{\mathrm{G}}\right) + \sum_{j\in C_b} \left(n'_j\right) r'_j + \sum_{j\in C_a} \left(n'_j\right) r_j}{\displaystyle N + \sum_{j\in A} n'_j \left(m_j - 1\right)} \tag{5.7}$$

where $n'_j = n_j + n_j^{ZEV}$ and $\sum_j n'_j = 0$, therefore the total number of vehicles N remains balanced.

Solving for the average emissions rate of the balancing vehicles, $\bar{r}'_j$, is analogous to Equation (5.4):

$$\bar{r}'_j = \frac{\displaystyle\bar{s}\left(N + \sum_{j\in A} n'_j \left(m_j - 1\right)\right) - \sum_{j\in C_b} n'_j \left(w_j p_j r_j^{\mathrm{A}} + \left(1-p_j\right) r_j^{\mathrm{G}}\right) - \sum_{j\in C_a} n'_j r_j}{\displaystyle\sum_{j\in C_a} n'_j} \tag{5.8}$$

The cumulative emissions γ^d [g CO_2], is nearly identical to scenario c in Equation (5.5) with the exception that the number of AFVs n_j is marginally increased/decreased by n_j^{ZEV}.

$$\therefore \gamma^d = \left(\left(\sum_{j\in A} n'_j \left(p_j r_j^{\mathrm{A}} \left(1-w_j\right) + \bar{s}\left(m_j - 1\right)\right)\right) + \bar{s}N\right) vl + \sum_{j\in A} n'_j \mu_j \tag{5.9}$$

5.2.2 Model input assumptions

Vehicle attribute inputs

Representative emissions rates and proportion driven on alternative fuels, r and p, for AFVs are obtained from the US Department of Energy (Table 5.6). We survey a range of peer reviewed-literature to estimate the incremental LCA emissions of battery emissions for electric vehicles μ (chosen as an average for technologies from Table 5.7).

Table 5.6: Summary of Vehicle Input Attributes[17]

Vehicle Make and Model	Vehicle Type	Gasoline Emissions Rate, r^{G} (grams CO_2/mile)	Alternative Fuel Emissions Rate, r^{A} (grams CO_2/mile)	Proportion of Operation on Alternative Fuel, p
†	FFV	221	221	0.50
Nissan Leaf	BEV	n/a	144	1
Toyota Prius	PHEV10	127	143	0.29
Chevrolet Volt	PHEV40	177	171	0.66
Honda Civic	CNG	n/a	345	1
††	FCV	n/a	170.6	1

†- Emissions from historical sales weighted emissions for all FFVs sold from 2002 through 2011.
††- Emissions from fuel utilization stage of fuel cell usage as measured in Granovskii et al. (2006), Table 8

Table 5.7: Life Cycle CO_2 Emissions from EV Lithium-ion Batteries

Source	Vehicle Type	kWh/kg battery	kg CO_2/kg battery
Notter et al. (2010)	BEV	0.11	6
Majeau-Bettez et al. (2011)	PHEV	0.11	22
Majeau-Bettez et al. (2011)	PHEV	0.09	22
Zackrisson et al. (2010)	PHEV	0.09	25
Hart et al. (2013)	PHEV	0.08	5
Hart et al. (2013)	BEV	0.1	16
Dunn et al. (2012)	PHEV	0.11	5.1
Dunn et al. (2012)	BEV	0.13	5.1

Vehicle usage over its lifetime

We employ the National Highway Transportation Survey (NHTS) for 2001 and 2009 to determine the average miles traveled per year for each year of the vehicles lifetime as seen in Figure 5.2.

The data also indicate that the average vehicle lifetime is approximately 9.3 years, providing an average lifetime VMT estimate of approximately 120,000 miles.

[17]The data are obtained using unadjusted fuel efficiency figures from the 2013 Fuel Economy Datafile from the Office of Transportation & Air Quality from the US EPA at http://www.fueleconomy.gov/feg/download.shtml, conversion to emission rates from kWh/100 miles by EPA conversion factors at http://www.epa.gov/cleanenergy/energy-resources/refs.html

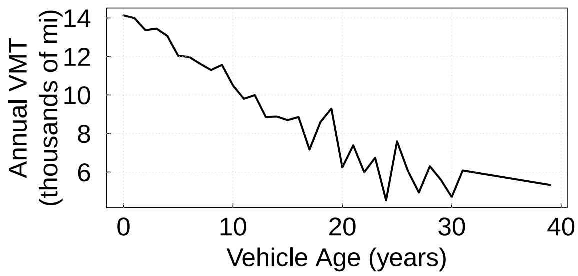


Figure 5.2: Average annual VMT by vehicle age from NHTS (2001 and 2009)

Vehicle sales projection

We model total emissions using sales projections generated by the California Air Resources Board 2050 Scenario Model[18]. We assume that the ZEV mandate is binding and therefore scenarios with the ZEV policy in place (Scenarios b and d) follow the sales projections made by CARB. The greatest source of uncertainty is from policy scenarios without a ZEV policy (Scenarios a and c). In these scenarios, we model total vehicles as identical but estimate a 50% reduction of AFV sales with sensitivity ranging from 0% to 100% of AFV sales in Scenarios b and d. We note that the sales figures resulting from a 50% estimate of CARB's projections is not without precedent: they roughly follow hybrid electric vehicle adoption rates over the last decade and reaches about 3% of the total market share over the course of 10 years. The sales assumptions for AFVs are displayed in Figure 5.3.

Estimating per manufacturer maximum potential increase in emissions

We base the maximum potential increase on the caps placed on the AFV incentives in the CAFE legislation. The caps are set on a per manufacturer basis with each manufacturer able to produce a cumulative quantity of 900,000 AFVs for each vehicle technology between 2012 and 2025 (300,000 cumulatively in periods 2012-2016, 2017-2021, and 2020-2025). We estimate the maximum possible contribution for a single manufacturer to increase emissions resulting from the combination of CAFE AFV incentives an exogenous policy mechanism

[18]Advanced Clean Cars AB1085 Background Materials for Emissions Data, Economic Data and Public Health Impacts. ZEV: ARB 2050 Scenario Model. http://www.arb.ca.gov/msprog/clean_cars/clean_cars_ab1085/clean_cars_ab1085.htm

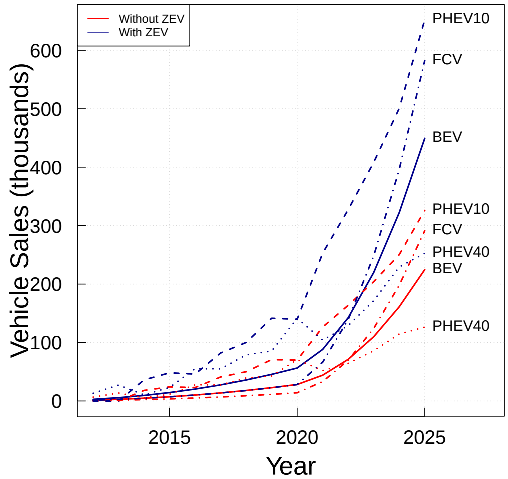


Figure 5.3: Annual vehicle sales broken down by technology with and without ZEV implementation, 2012-2025.

that induces high levels of AFV adoption such as ZEV.

Projecting total emissions increases from CAFE and a nationwide "ZEV-like" mandate

We consider a final policy scenario in which we model individual state contribution to increased emissions by compliance with CARB ZEV requirements in Table 5.4 (in the case where all other states adopt a policy similar to Californias ZEV program). The same major manufacturers facing the full ZEV compliance mandates are used for all states (Ford, Honda, GM, Nissan, and Toyota).

For our sales estimates, we use average sales of manufacturers from 2002 through 2011 on a state-by-state basis as annual sales figures through 2025. While the modeling using CARB's sales projections is likely to be more accurate for California and 177 states, the state-level estimates provide a reference point for relative state contributions to emissions increases due to the policy interaction.

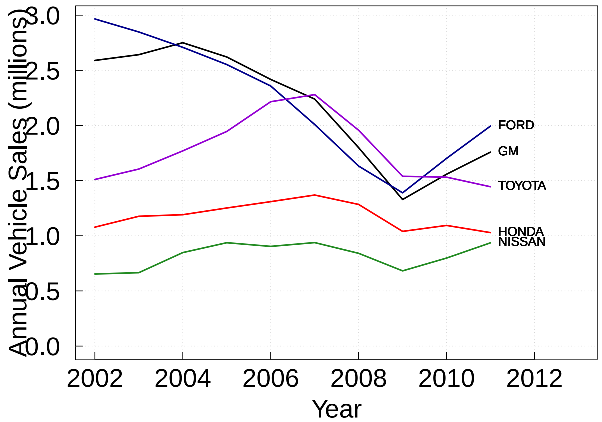


Figure 5.4: Historical annual sales of major vehicle manufacturers

5.3 Results

5.3.1 Vehicle emissions from policy scenarios $a - d$

Our results indicate that the interaction of CAFE AFV incentives and ZEV mandates will likely lead to cumulative increases of over 100 million metric tons of CO_2 for vehicles sold between 2012 and 2025. Figure 5.5 provides a breakdown of total emissions for new vehicles sold. The slight differences between Scenarios a and b are a result of slightly higher lifetime emissions for AFVs, particularly for electric vehicles whose batteries result in higher emissions in the production phase of the vehicle compared to traditional ICVs. The uncertainties in Scenarios a and c are due to uncertainty in the number of AFVs sold in the absence of the ZEV mandate. Counter-intuitively, the greater the success of the ZEV policy in increasing the sales of AFVs, the greater the emissions penalty resulting from the AFV incentives in the CAFE policy.

Figure 5.6 displays emissions increases for all policy scenarios relative to Scenario a with only CAFE standards in place. The ZEV mandate alone (Scenario b) does not increase emissions much, despite the large increase in AFVs since the use-phase emissions will be equivalent to Scenario a.

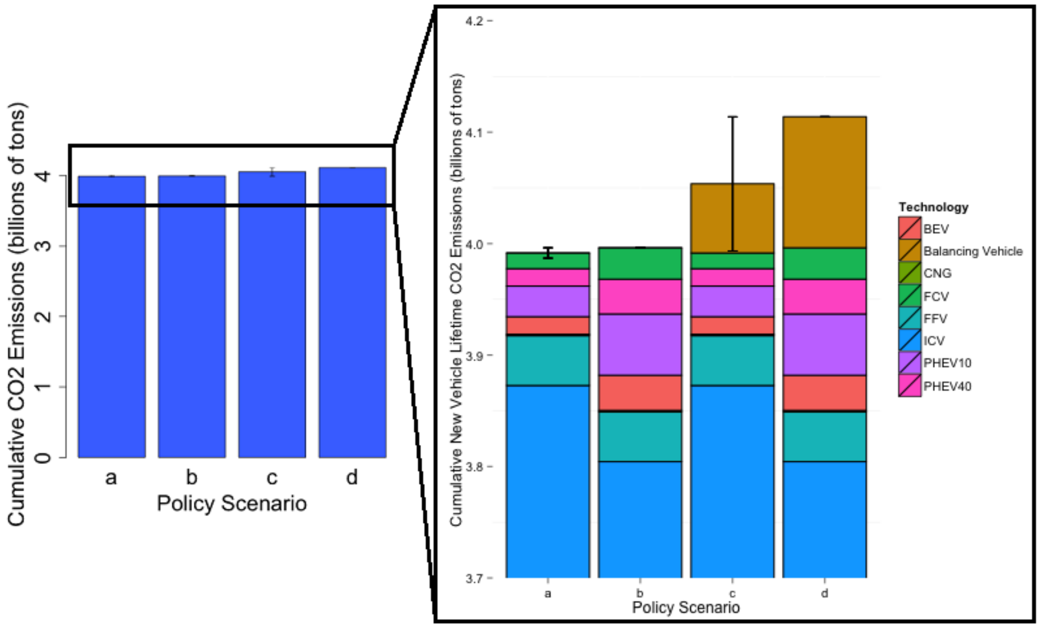


Figure 5.5: Cumulative lifetime emissions for new vehicles sold from 2012 through 2025, broken down by technology. Scenarios (all with CAFE standards): *a* no AFV incentives, no ZEV mandate; *b* no AFV incentives, ZEV mandate in place; *c* AFV incentives in place, no ZEV mandate; *d* both AFV incentives and ZEV mandate in place.

5.3.2 Maximum potential emissions increase from a single manufacturer

Based on the maximum allowable use of AFV incentives per manufacturer, we are able to estimate the maximum potential emissions increases for vehicles sold in each cap period. Given a manufacturer can take advantage of 900,000 vehicles worth of AFV credits, the highest emissions increase from a single manufacturer is approximately 65 million metric tons of CO_2. Vehicles contributing to emissions can be broken down into three periods (each with a cap of 300,000 cumulative vehicles sold) as seen in Figure 5.7. The increased emissions in the 2017 to 2021 period are a result of higher multipliers and weights for AFVs during the period (refer to Table 5.2).

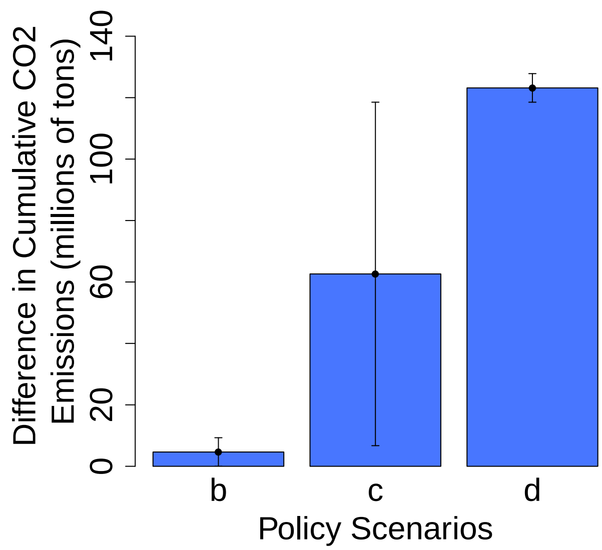


Figure 5.6: Relative increases in emissions compared to policy scenario with CAFE without AVIs and no ZEV implementation, cumulative lifetime emissions for new vehicles sold from 2012-2025.

5.3.3 State level emissions increases from adoption of "ZEV-like" policy with existing CAFE AFV incentives regime

Using historical state level vehicle sales and a strict ZEV compliance path (see Table 5.4), we estimate the emissions increase on a state-by-state level for the five major manufacturers that are subject to the full ZEV regime (Ford, Honda, GM, Nissan, and Toyota). The cumulative emissions in Figure 5.8 demonstrate potential increases if any state adopts the equivalent CARB ZEV policy while benefitting from AFV incentives. While relative differences are driven largely by population differences, the relative contribution of manufacturers differs from state-to-state (e.g. Japanese companies Toyota, Honda, and Nissan comprise the bulk of contributing emissions in California while in Michigan the emissions are almost entirely from Ford and GM).

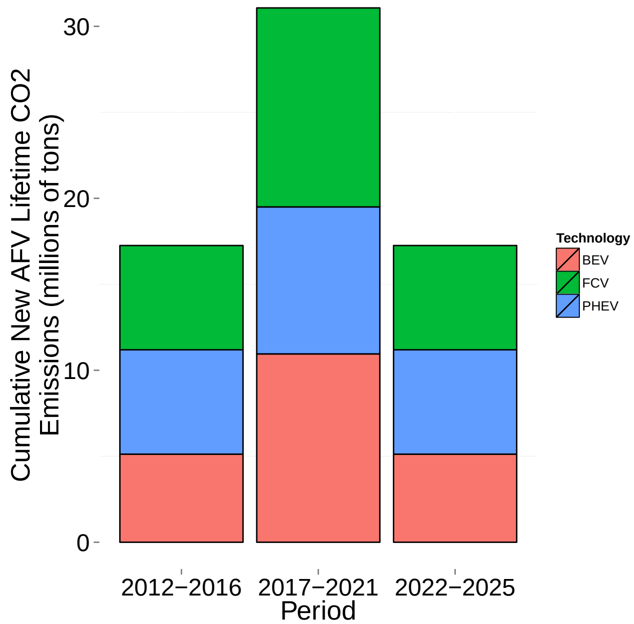


Figure 5.7: Per manufacturer maximum possible increase in emissions from selling AFVs (BEVs, PHEVs, and FCVs).

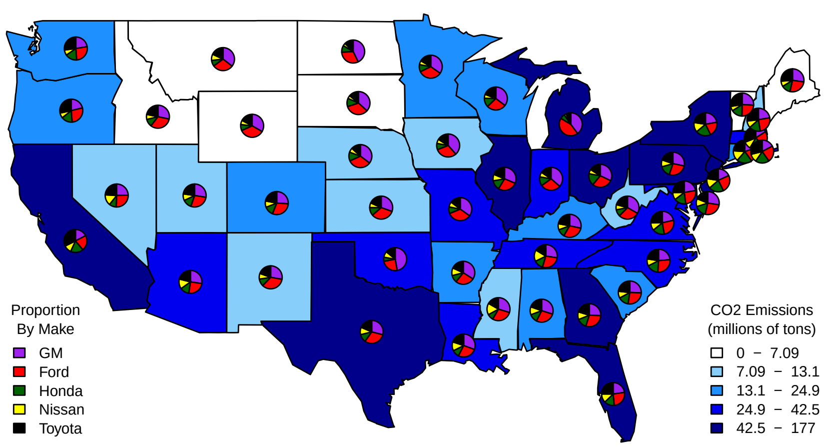


Figure 5.8: State level cumulative increases in emissions over lifetime of AFVs sold from 2012-2025.

5.4 Conclusion

In our analysis of current policies promoting the sale of alternative fuel vehicles, we find that the interaction of CAFE with AFV incentives and the ZEV program in California leads to unintended increases in vehicle emissions. The presence of AFV incentives in the CAFE legislation in conjunction with the ZEV mandates results in emissions increases to over 120 million tons of CO_2: equivalent of forty typical coal power plants operating for one year and over 10% of the estimated savings 900 million tons of CO_2 from the CAFE standards. The interaction of such policies would allow an individual manufacturer to potentially increase emissions by as much as 65 million metric tons of CO_2 over the lifetime of new vehicles sold between 2012 and 2025. While such limits are unlikely to be reached, states that are considering mandatory compliance scenarios such as ZEV will unintentionally increase short term vehicle emissions in the US. While many of our results are based on inherently uncertain AFV sales projections from the California Air Resources Board, we are able to demonstrate the counterintuitive effect where the greater the success of ZEV in promoting the adoption of AFVs, the greater the increase in emissions due to the AFV incentives in the CAFE rule.

Modeling the complexities of different policy scenarios is a difficult task, in particular when considering what the standard of comparison should be. It should be noted that our estimates of emissions increases of 120 million tons of CO_2 is against a baseline of CAFE without incentives (as well as without ZEV). However, it may be the case that had CAFE passed without any incentives in place, the standards may have taken some other form and perhaps been less stringent. In addition, in comparison to a scenario in which CAFE standards were not altered during the 2009 update, our baseline would actually result in large emission savings which would likely not be offset by the presence of incentives and/or the implementation of ZEV. Finally, considerations of emissions in the absence of CAFE entirely are particularly difficult, as we have no information on the adoption of alternative fuel vehicles in such a scenario.

Perhaps the most important consideration is the original intent of the policies and whether interactions of policies confound them. While there are significant uncertainties as to the efficacy of CAFE incentives and the ZEV mandate (among other policies that promote the adoption of AFVs), if it is the case that one policy such as the ZEV mandate is a binding constraint, then the inefficiencies of the CAFE AFV incentives can in theory be avoided. Future efforts to model AFV adoption in different policy regimes can help to shed light on this issue.

The intention of our work is not to discredit the implemented policies but to shed light on unintended consequences of their interaction. We acknowledge the long-term benefits such as those described in Greene et al. (2013) from the implementation of policies such as CAFE and ZEV, but we seek to quantify some of the short-term costs in order to better inform future policy decisions. It may be the case that such unintentional policy interactions can be accounted for and promotion of AFV sales can be carried out in a more efficient manner. In addition, for states that are contemplating legislation to promote AFV adoption, our analysis can contribute to the policy making process by shedding light on the potential emissions impacts.

Chapter 6

Heterogeneity of gasoline price elasticities, a case study in Pennsylvania

6.1 Introduction

The United States annually consumes over 130 billion gallons of gasoline, the vast majority of which is used in the transportation sector. The use of fossil fuel in transportation leads to nearly 2 billion metric tons of CO_2 being emitted into the atmosphere every year in the US. Policy-makers and regulatory agencies have implemented measures such as the Corporate Average Fuel Efficiency standards and the Zero Emissions Vehicle mandate (policies promoting higher efficiency or alternative fuel vehicles), as well as the Renewable Fuel Standards and Low Carbon Fuel Standards (policies promoting the use of alternative fuels) in an effort to curb oil consumption and carbon emissions.

Our work focuses on consumer responsiveness in terms of driving intensity, specifically with a focus on gasoline prices. This is particularly useful for policy-makers to understand the effects of exogenous shocks such as gas taxes, but the uniqueness of our work aims to understand the heterogeneity of response across different criteria. How does driving behavior change with a marginal change in fuel prices if gas prices are already high? Or already low? How do drivers who travel a lot compare to drivers who drive few miles annually respond to price changes?

Gasoline price elasticities describe changes in driving intensity in response to changes in the price of gasoline. Studies of gasoline elasticities span several decades, many of which are described in the vehicle rebound literature. The rebound effect is a result of increasing the energy efficiency of a service but instead of seeing a corresponding decrease in the resource consumption, the consumer views the service as being cheaper and hence it is used more. In transportation, the efficiency increase is typically due to improvements in the fuel economy of the vehicle and the offset in savings benefit is due to an increase in miles driven. Gasoline elasticities are an important aspect of rebound studies as they are often assumed as proxies for the fuel efficiency changes as a change in the overall cost of driving.

The vast majority of literature in the area can be grouped into elasticity estimates obtained through surveys or by large aggregated sets of data. In the latter category, Dahl and Sterner (1991) perform one of the earliest review pieces that consolidates findings of gasoline demand elasticities from studies in 1979 through 1991. Based on a survey of studies on gasoline demand, the authors standardize the studies into a static model formulation that indicates an average short run elasticity of -0.26 and a long run elasticity of -1.02. A more recent review by Greening et al. (2000) covers analysis spanning from 1967 through 2000 and finds long run elasticities in the range of -0.09 to -0.31. However, the initial studies characterized in the review from Dahl et al. and Greening et al. used relatively simple specification models, often ignoring issues of endogeneity.

More recently, a number of rigorous studies on vehicle rebound have been published. In a paper by Small and Van Dender (2007), the authors incorporate variance through income, urbanization, and the cost of driving with simultaneous equations in the US using the periods of 1967 through 2001 and a short run examination using the periods from 1997 through 2001. They estimate short run rebound effects of approximately 4.5% and long run effects of 22.2%. The rigorous approach by the authors capture the endogeneity of fuel efficiency, an identification problem where fuel efficient vehicles may encourage more driving while drivers who expect to drive more will purchase fuel efficient vehicles. Similarly, a recent study by Linn (2013) identifies three critical assumptions that are often overlooked by vehicle rebound studies: fuel efficiency is likely correlated to other vehicle attributes, travel behavior is not independent between vehicles for multi-vehicle households, and that behavior does not respond identically between fuel efficiency and gasoline prices. When these assumptions are properly accounted for, Linn finds a .2% to .4% increase in driving resulting in a 1% increase in fuel economy.

Unfortunately, vehicle transportation records are typically low in resolution and do not capture behavioral variance throughout large populations. There are very few studies that do not rely on aggregated data or surveys. In one such study, Knittel and Sandler (2013) consider applications of behavioral responses to price changes in gasoline by estimating the impact of a Pigouvian tax. The authors find average elasticities of -0.15 but show that the dirtiest vehicles respond quite differently with an elasticity of -0.29. They demonstrate that a non-uniform tax is optimal due to the fact that dirtier cars respond more the gasoline taxes and a uniform Pigouvian tax does not eliminate deadweight loss efficiently. In another study, Gillingham (2013) uses a California vehicle registration dataset similar to the inspection dataset we use in our analysis, the author estimates elasticity of vehicle miles travelled with respect to gasoline prices to be in the range of -0.15 to -0.20. Figure 6.1 displays average point estimates of gasoline elasticity studies spanning the last decade. The range of response to fuel price changes is quite large, despite our omission of even more extreme elasticity outliers.

We focus specifically on the heterogeneity of gas price elasticities. Examination of this issue has been studied in a small number of works over the last decade. Gately and Huntington (2001) examine asymmetry of gas price elasticity at a macro-level over ranges of income

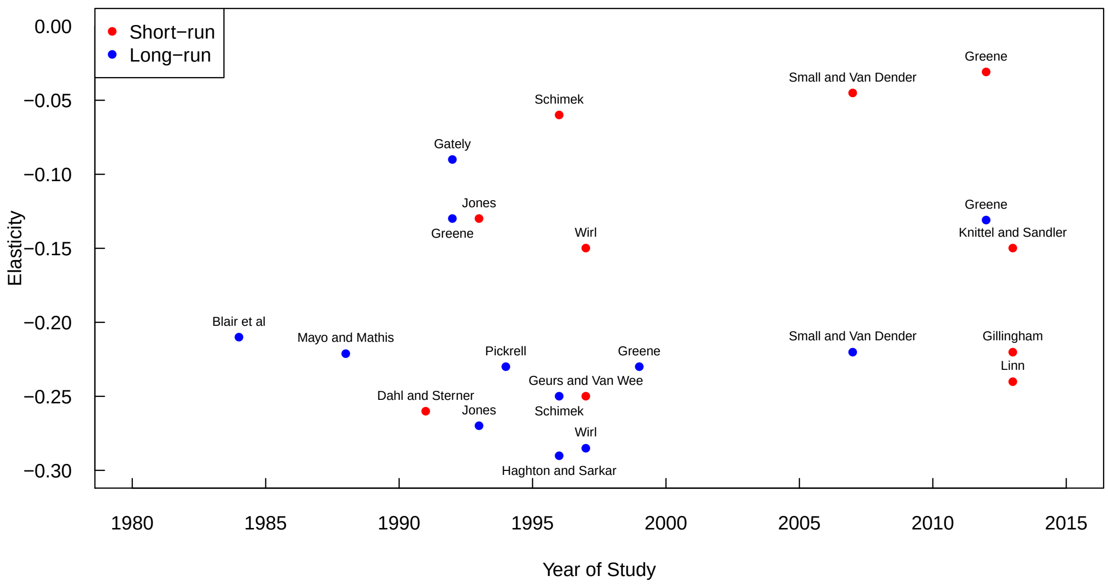


Figure 6.1: A review of average gasoline price elasticities in the literature

growth between different countries. Long-run elasticities are found to vary greatly between countries, as low as -0.20 to -0.71. Frondel et al. (2012) investigate differences in rebound effects across strata of household driving intensity using survey diary data from Germany. The authors perform a quantile regression based on driving distances and finds that elasticity decreases as a function of driving intensity: for the lowest intensity elasticity is measured to be about -0.9 falling to -0.56 for the highest driving intensity. Most recently, Lin and Prince (2013) investigate changes in consumer response to gasoline prices depending on the volatility of the prices. During periods of high volatility (2007-2012), the elasticity is nearly twice as high at -0.052 compared to periods of low volatility (2000-2006) with an elasticity of -0.03.

Our work expands on existing research by using empirical data from Pennsylvania with a comprehensive dataset and highly variable monthly fuel prices. Rather than estimating the average gasoline price elasticity as in the majority of the literature, we investigate the heterogeneity in driving behavior. We follow the approach in Frondel et al. by examining the relation between driving intensity and gasoline prices. However, we complement the analysis with an additional examination of the elasticity asymmetry over ranges of fuel price levels and vehicle fuel efficiencies. The remainder of the chapter is organized as follows: Section 6.2 is a description of the datasets used in our analysis as well as summary statistics of the data. Section 6.3 follows with an explanation of the regression approaches we employ for our estimation of elasticities. Lastly, Sections 6.4 and 6.6 present our findings and a discussion of the results.

6.2 Data

6.2.1 Pennsylvania Department of Transportation (PennDOT) Data

Vehicle owners in Pennsylvania are required to undergo annual emissions inspections for their vehicles. The inspections consist of: an On-Board Diagnostics (OBD) Inspection and Maintenance (I/M) check where a technician attaches a cable to the onboard computer to observe whether emissions equipment is damaged; a visual check of the catalytic converter, exhaust gas recirculation valve, positive crankcase ventilation valve, fuel inlet restrictor, air pump, and evaporative control system components; and lastly a gas cap test to ensure the vehicle gas cap is sealed properly[1]. Inspections stations throughout Pennsylvania were required to purchase equipment for OBD I/M checks in 2003 and 2004, which also had the benefit of electronically recording emissions and other vehicle information at the time of inspection.

We obtained a large dataset from PennDOT containing over 75 million vehicle emission inspection records in Pennsylvania from 2000 through 2010 as well as 40 million registration records in 2011. The resolution of these data is nearly unprecedented as nearly all other studies on elasticity are based on survey or aggregated data. The individual vehicle level data offers us several advantages: we are able to fully capture variance in the population,

[1]Pennsylvania Region Fact Sheets. http://www.drivecleanpa.state.pa.us/changes/fs_philadelphia.pdf

we avoid many issues of self-reported driving behavior in surveys, and we are able to track vehicles over very long periods of time. Each record contains a Vehicle Identification Number (VIN), a code assigned to every individual vehicle that gives a unique identifier as well as comprehensive information on vehicle attributes. The first three characters in the VIN are the manufacturer identifier, the next five digits give general characteristics of the vehicle with a check digit in the ninth position, and tenth and eleventh characters are typically year and plant manufacturing codes, and finally the last set of digits give the serial unique identifier (see 6.1).

Table 6.1: Breakdown of VIN Digits

Vin Digit	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
	Manufacturer			Vehicle Attributes					Check Digit	Model Year	Plant Code	Unique ID					

While the set of vehicle characteristics provided directly from the data is somewhat limited, information about the vehicle can be obtained from the vehicle identification numbers (VINs). Using a VIN decoder[2] we are able to obtain a comprehensive set of vehicle characteristics and attributes. From the decoder, we extracted a detailed set of information including the make, model, year, manufacturing country, body style, body type, engine type, engine size, fuel type, drive type, highway miles per gallon (MPG), city MPG, weight, fuel tank size, and manufacturer's suggested retail price (MSRP). In addition, the data allow us to track individuals by single vehicles on an approximately annual basis (since inspections in Pennsylvania are required once a year) with resolution at the daily level.

Figure 6.2 reveals a possible issue with selection bias: due to the changes in the inspection program over time, the sample of drivers may misrepresent the actual population of drivers. The data contain only 60% of all registered in Pennsylvania in the latter half of our records

[2]Using a data scraper from www.decodethis.com

[3]Full list of exempted counties can be found: http://www.drivecleanpa.state.pa.us/map.htm

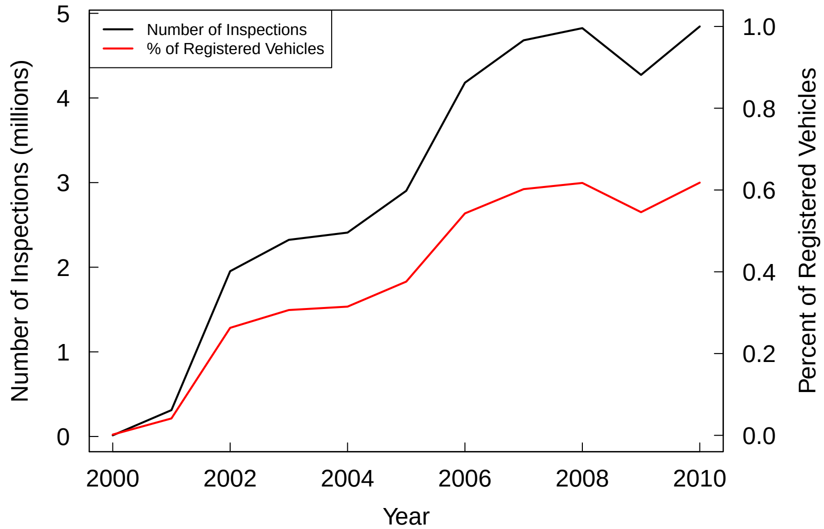


Figure 6.2: Count of inspection records and percentage of total registered vehicles by year by year[3]

but prior to 2002 contain less than 20% of registered vehicles. The missing records are in part due to emissions exemptions for vehicles older than 16 years and by individuals who choose not to inspect their vehicles. However, the majority of missing records are the result of inspections that are not recorded (as is the case for most manual inspections prior to the implementation of OBD I/M) and residents in PA who live in areas where inspections are not required. In addition, the sampling differences are substantially biased by location with inspection records prior to 2003 almost solely located in urban regions as seen in Figure 6.3. By 2004, the OBD inspections were rolled out through most rural counties in central, northwestern, and southeastern Pennsylvania. As a result of the missing data, our elasticity values are likely to be biased towards urban and suburban results as many rural areas in PA are missing.

We address the possibility of selection bias by grouping the inspections into several vehicle cohorts. The cohorts are selected such that all vehicles within a selection must appear in the inspection records every year without missing an inspection. For example, the group of

[4]Full list of exempted counties can be found: http://www.drivecleanpa.state.pa.us/map.htm

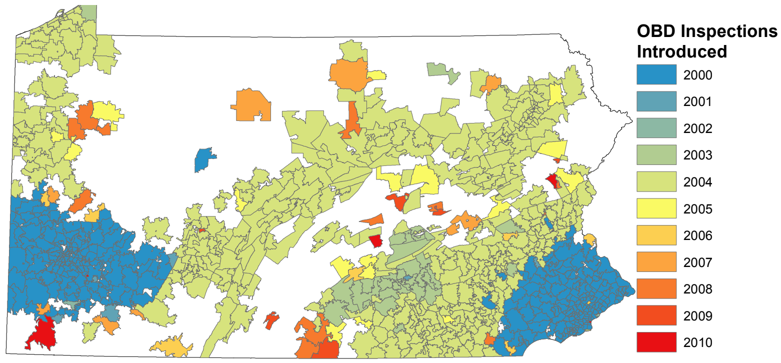


Figure 6.3: Expansion of inspections requirements from 2000 through 2010[4]

vehicles from 2002 through 2010 represents all cars that appear in the inspections records every year from 2002 through 2010–thus maintaining a uniform sample over time. We select two cohorts of vehicles: 2002-2010 and 2006-2010. The 2002-2010 cohort is a relatively smaller sample but maximizes the longitudinal observations of the data so that all vehicles are observed for a period of nine years. We note that the results from the 2002-2010 cohort will likely differ from the 2006-2010 cohort due to the difference in regional coverage (see Figure 6.3), as the former set is primarily confined to more urban areas. The 2006-2010 cohort is longitudinally shorter, but contains a far larger number of observations due to its larger regional coverage. Table 6.2 contains summary statistics of the two cohorts. We observe slightly higher annual VMT, younger cars, and slightly lower fuel efficiency in the latter cohort.

We provide some basic visualization of the data in Figures 6.4 through 6.6. Figure 6.4 provides a snapshot of observed vehicle counts broken down by ZIP codes in 2010. In total there were 4.8 million vehicles in the emissions inspections records in 2010, approximately 60% of the registered vehicles in PA (see Figure 6.2). Counts by ZIP code are closely related to the population density: Pittsburgh and Philadelphia have the highest density of vehicles in the southeastern and southwestern quadrants of the state respectively. Figure 6.5 shows the average annual vehicle miles travelled by ZIP code using vehicle inspections in Pennsylvania

[5]Full list of exempted counties can be found: http://www.drivecleanpa.state.pa.us/map.htm

Table 6.2: Summary Statistics[5]

	2002-2010		2006-2010	
	Mean	Std Dev	Mean	Std Dev
Annual Average VMT [mi]	8,690	6,150	9,330	6,730
Odometer [mi]	81,900	44,700	81,200	44,700
Average Gasoline Price [$/gal]	2.3	0.59	2.76	0.3
Age [yr]	9.41	3.94	8.97	3.94
Fuel Efficiency [mi/gal]	23	4.88	22.8	4.99
Average Unemployment Rate	5.63	1.18	5.77	1.54
Average GDP	14,100	737	14,600	216
n	1,761,358		7,241,499	

from 2000 through 2010. We observe higher driving intensity in rural areas compared to urban areas. Lastly, Figure 6.6 provides the average fuel efficiency by ZIP in 2010. There does not appear to be an immediate spatial trend with fuel efficiency though the variance of fuel efficiency is quite small across the entire state.

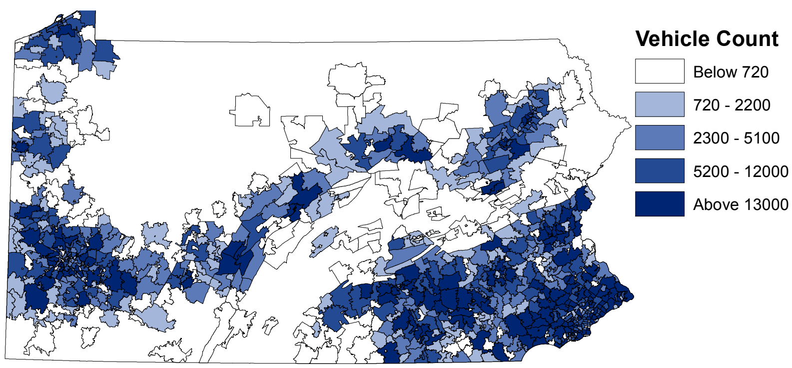


Figure 6.4: Vehicle count in ZIPs with vehicle inspections in PA (2010)

We calculate the vehicle miles travelled for every car by computing the difference in odometer readings from year to year. As a result a single observation per vehicle is dropped, as the first odometer value cannot be used to determine a VMT. Since the inspections reporting occurs on only an approximately annual basis, we scale each of the VMTs to reflect 365 days of driving. We compute the difference between VMTs for each individual vehicle to assess annual variability in driving patterns. In our analysis, we truncate our data

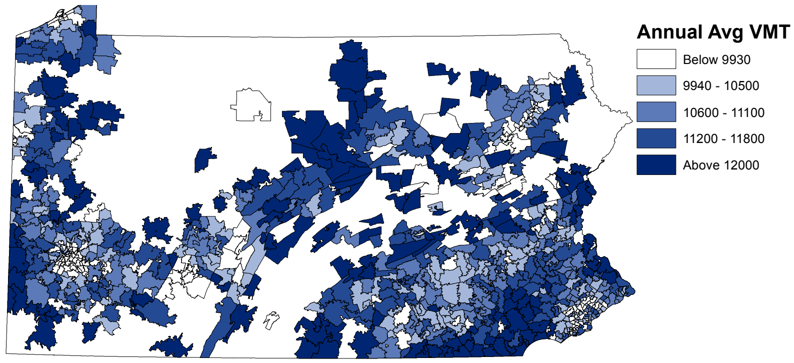


Figure 6.5: Average annual VMT per vehicle in ZIPs with vehicle inspections in PA from 2000-2010

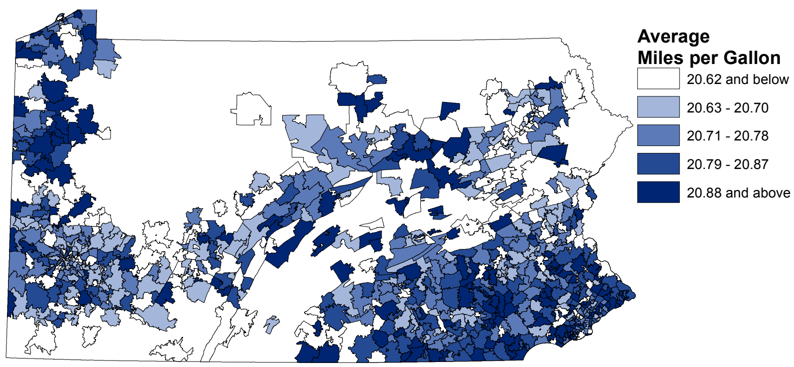
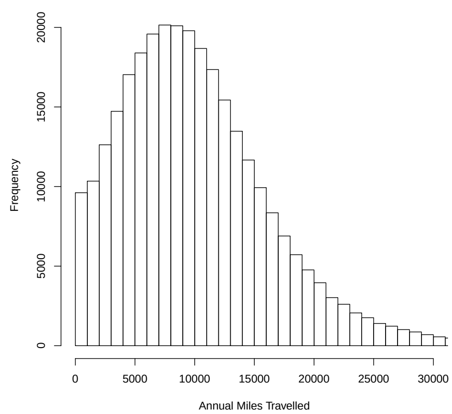


Figure 6.6: Average fuel efficiency in ZIPs with vehicle inspections in PA from 2000-2010

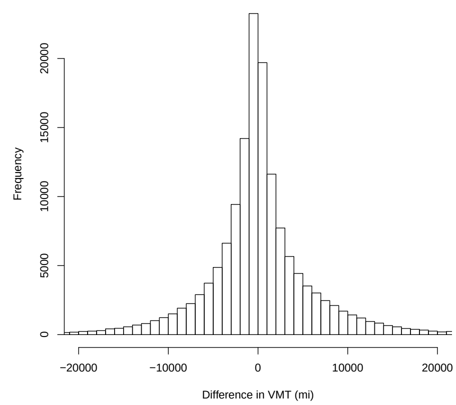
and drop observations where vehicles were not used (VMT of 0, $< 1\%$), as well as vehicles with VMT of greater than 200,000 miles or odometer readings of greater than 7,000,000 miles ($< 0.01\%$), which are likely inspection reporting errors.

Figure 6.7 displays several visual summaries and trends of driving intensity behavior in Pennsylvania. In Figure 6.7 (a), we display a histogram of annual VMTs over the entire dataset. The VMTs closely follow a truncated normal distribution with mean annual driving of slightly over 10,000 miles per year. However, Figure 6.7 (b) displays a relatively surprising trend: the change in annual VMT is highly variable, with a large number of vehicles where the number of miles driven changes by as much as 20,000 miles per year. This is mainly attributed to variability in driving, but also in part due to the fact that we are tracking vehicles and not vehicle owners and therefore do not account for transfers of vehicle ownership.

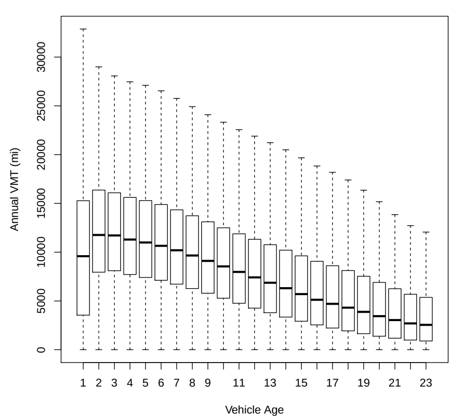
We also observe large changes in annual VMT behavior over the age of the vehicle in Figure 6.7 (c). The average VMT by an individual continuously decreases over the lifetime of the vehicle, though the variance of driving spans a large range over the entire sample population. Lastly, in Figure 6.7 (d) we display differences in VMT over time and find that driving behavior seems to be relatively constant with the exception of 2000.



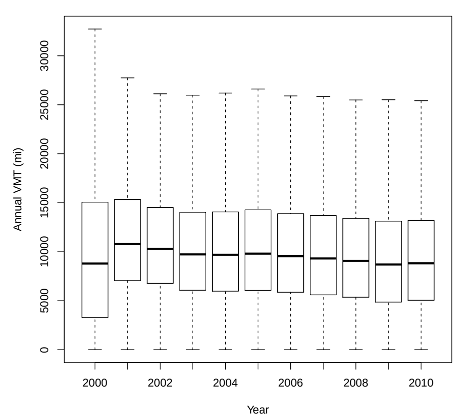
(a) Histogram of Annual VMT



(b) Histogram of Changes in Annual VMT



(c) Boxplot of VMT by vehicle age

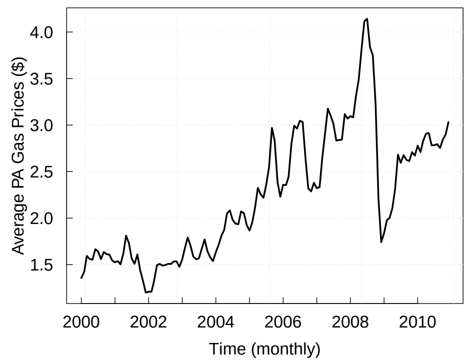


(d) Boxplot of VMT by year

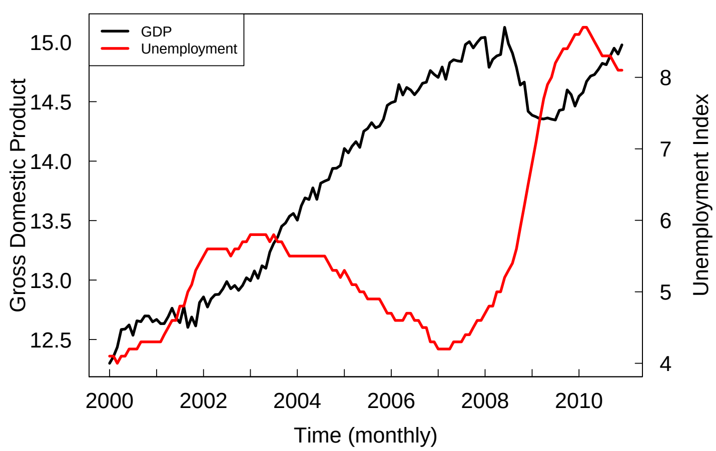
Figure 6.7: Annual vehicle miles travelled trend graphs in PA from 2000 through 2010.

6.2.2 Other data

In Figure 6.8, we display macroeconomic trends from 2000 through 2010. We include these trends in our model to account for how driving intensity is affected by general economic indicators. Note that our period of observation includes large variance in these trends due to the US economic recession occurring in the latter half of the 2000's.



(a) PA Real Gasoline Prices, 2000-2011



(b) US Gross Domestic Product and Unemployment Rates (seasonally adjusted), 2000-2011

Figure 6.8: Macroeconomic variable time trends (real in 2013 dollars)

For gasoline prices, we used monthly prices[6] for the state of Pennsylvania from 2000 through 2010. We then calculate the average gasoline price a consumer faced between each

[6]US Energy Information Administration: Independent Statistics & Analysis, Pennsylvania Monthly Retail Gasoline Prices

inspection period. For example, for an individual who inspected their car in January of 2000 and January of 2001, we take the average price of the monthly prices between the two inspection periods to determine the average price subjected to that individual. A vector of average gas prices is then generated for each corresponding VMT value. We perform a similar operation on other macroeconomic variables that change over time such as gross domestic product (GDP)[7] and unemployment rates[8]. Lastly, we capture demographic attributes broke down at the ZIP code level. We collected the 2011 American Consumer Survey (ACS) 5-year estimates and the 2000 US Census for a variety of factors including population statistics, education, income, and commuting behavior. Commuting information includes population who commute to work, whether they drive alone, carpool, take public transportation, walk, or some other means of transportation. A quadratic interpolation was used to estimate for periods between 2000 and 2010.

6.3 Methods

6.3.1 Specification Strategy

Our primary specification model describes the vehicle miles travelled VMT_{it} for a car i for time t as a function of the average price of gasoline a vehicle faced from its inspection in time t to its previous inspection, gas_t; a vector of macroeconomic variables, $\mathbf{M}_t$ (GDP and unemployment); time variant vehicle attributes, V_{it} (age); a vector of time varying demographic attributes, $\mathbf{V}_t$ (education, income, and commuting behavior); vehicle-level fixed effects, θ_i; and monthly fixed effects, η_t. We model the relationship using a log-log specification:

$$\log\left(VMT_{it}\right) = \alpha \log\left(gas_{it}\right) + \vec{\beta}\log\left(\mathbf{M}_t\right) + \vec{\gamma}\left(\mathbf{V}_{it}\right) + \vec{\zeta}\left(\mathbf{D}_{it}\right) + \theta_i + \eta_t + u_{it} \tag{6.1}$$

where u_{it} is the mean-zero error term. The vehicle-level fixed effects capture time-

[7]Macroeconomic Advisers: Monthly GDP Index

[8]Bureau of Labor Statistics: Unemployment Rate for States

invariant variables such as vehicle attributes (make, model, fuel efficiency, etc.) and time-invariant location based fixed effects (since only a very small number of vehicles change locations in our data). By taking advantage of the high resolution of our data, we are able to capture a tremendous amount of variation at the vehicle level and at the ZIP code level with fixed effects on individual vehicles (θ_i) and focus on our attributes of interest. In addition, the monthly fixed effects, t, help to capture time-based uniform effects over all vehicles in Pennsylvania.

The coefficient α represents the elasticity of VMT with respect to driving intensity and is the primary effect of interest in our study. However, we break down the determinants of elasticity of driving, beyond its average effect by examining differences in responses over levels of driving intensity, gasoline prices, and fuel economies. We take two approaches in examining the heterogeneity of elasticity: using subsamples of data and interacting gasoline prices with categorical variables.

Subsampling of data

We estimate the model described in Equation (6.1) using subsamples of the data for each of the factors we believe contribute to the heterogeneity of elasticity. For driving intensity, we run the model separately for subsets of data where $i \in \{VMT_{it}^{Q1}$, VMT_{it}^{Q2}, VMT_{it}^{Q3}, VMT_{it}^{Q4}, $VMT_{it}^{Q5}\}$ where $Q1-5$ represent quantiles of average VMTs for a single vehicle (a single vehicle is categorized by its average VMT and cannot be placed in separate categories over time). For fuel economy (FE), we run the model separately for subsets of data where $i \in \{FE_{it}^{Q1}$, FE_{it}^{Q2}, FE_{it}^{Q3}, FE_{it}^{Q4}, $FE_{it}^{Q5}\}$ where FE is the fuel economy of vehicle i and $Q1-5$ represents quantiles of fuel economies by vehicle. Table 3 displays the quantile values upon which we divide the data.

In this subsampling approach, each set of fixed-effects regression results will have a value of that represents the elasticities among groups of vehicles that differ by their relative driving intensity as well as fuel economy.

Table 6.3: Quantile values for subsamples

	VMT [mi]	FE [mi/gal]
$Q1$	0–5,840	0–18
$Q2$	5,840–8,570	18–21.5
$Q3$	8,570–11,100	21.5–24
$Q4$	11,100–14,500	24–27
$Q5$	>14,500	>27

Interactions approach

We modify Equation (6.1) to include interactions $\mathbf{I}_{it}$ based on the factors of interest:

$$\log\left(VMT_{it}\right) = \alpha \log\left(gas_{it}\right) + \vec{\mu}\left(\log\left(gas_{it}\right) \times \mathbf{I}_{it}\right) + \vec{\beta} \log\left(\mathbf{M}_t\right) + \vec{\gamma}\left(\mathbf{V}_{it}\right) + \vec{\zeta}\left(\mathbf{D}_{it}\right) + \theta_i + \eta_t + u_{it} \tag{6.2}$$

We use this model to estimate differences in elasticities across different gasoline price levels and vehicle fuel economy levels. In the model estimating elasticities across ranges of gas prices, $\mathbf{I}_{it}$ is a categorical variable with levels defined as: $\{gas_{it}$ <\$1/gal, \$1/gal< gas_{it} <\$2/gal, \$2/gal< gas_{it} <\$3/gal, \$3/gal< gas_{it} <\$4/gal, gas_{it} >\$4/gal$\}$. Similarly, in our model estimating elasticities across ranges of vehicle fuel economies, $\mathbf{I}_{it}$ is a categorical variable with levels defined as: $\{FE_{it}$ <20 MPG, 20 MPG< FE_{it} <30 MPG, 30 MPG< FE_{it} <40 MPG, FE_{it} >40 MPG$\}$.

The values of μ represents the heterogeneity in gas price elasticities across the fuel economies and gasoline price levels. Differences in elasticity values indicate that the responsiveness to changes in gasoline prices is not uniform.

6.3.2 Identification issues

Due to our datasets resolution at the vehicle level, time-constant sources of endogeneity are entirely accounted for with vehicle-level fixed effects—which can be especially problematic in modeling approaches employing aggregated data. However, we also include a number of important time-variant controls: unemployment, GDP, and monthly fixed effects. Unemployment and GDP act as controls for macroeconomic factors that can influence individual driving intensity while the monthly fixed effects help to control for other uniform time effects that may influence driving behavior.

Another important identification issue is whether gasoline prices in Pennsylvania are locally independent of individual driving behavior. In our study, we assume that vehicles are strictly price takers since oil prices are determined by global demand and supply: local Pennsylvania demand changes would negligibly affect gas prices.

6.4 Results and Discussion

6.4.1 Heterogeneity of gasoline price elasticity over ranges of driving intensity

Our first approach examines the gasoline price elasticity with respect to driving intensity over different ranges of annual VMT travelled. The results of our regression are displayed in Table 6.4 and Table 6.5 for the cohort of vehicles inspected in 2002-2010 and 2006-2010 respectively. The average gas elasticities for the model run on the full data for the two cohorts are relatively close at -.131 for 2002 and -.117 for 2006 and are statistically significant at p=.01. However, when we break down the data into quantiles of VMT, we observe substantially different elasticity values. Vehicles in the 2002 cohort are more responsive, with elasticities as high as -.767 in the model on the quantile of lowest driving intensity, though the upper quantiles are only statistically significant at p=.1 and p=.05 (Q4 and Q5 in Table 6.4). In comparison, the most responsive drivers in the 2006 cohort are still those in the quantile of lowest driving intensity but with a lower elasticity value of -.172. While the overall magnitude of responses are slightly different between the two cohorts, we find a consistent trend in both models where responsiveness to changes in gas prices decreases as driving intensity increases. The general trend indicates a non-uniform response to gas prices, specifically a decrease in elasticity as driving intensity increases. Individuals who drive less on average may be more flexible with their mode of transportation (or transportation requirements), and therefore they are more apt to react to changes in fuel prices in comparison to drivers who are required to travel farther annually on average.

Table 6.4: Regression results on log(VMT), 2002–2010 data separated by quantiles of VMT with monthly and vehicle level fixed effects (demographics omitted) with clustered standard errors by ZIP codes[9]

Variable	Full	VMT_{it}^{Q1}	VMT_{it}^{Q2}	VMT_{it}^{Q3}	VMT_{it}^{Q4}	VMT_{it}^{Q5}
log(gasprice)	-0.131***	-0.767***	-0.425***	-0.209***	-0.0617*	-0.117**
	(0.0182)	(0.0509)	(0.037)	(0.033)	(0.0351)	(0.0484)
log(unemp)	0.374***	-0.662***	0.308***	0.751***	0.905***	0.888***
	(0.0136)	(0.0296)	(0.024)	(0.0276)	(0.0335)	(0.051)
log(GDP)	5.42***	3.65***	7.54***	8.21***	7.32***	9.7***
	(0.103)	(0.251)	(0.197)	(0.204)	(0.244)	(0.377)
log(age)	0.383***	0.134***	0.279***	0.164***	0.125***	0.128***
	(0.00385)	(0.0084)	(0.00821)	(0.00799)	(0.00894)	(0.0141)
Adj R Sq	0.665	0.586	0.168	0.076	0.0709	0.139
n	1,570,869	406,482	365,033	370,371	292,408	136,131

Table 6.5: Regression results on log(VMT), 2006–2010 data separated by quantiles of VMT with monthly and vehicle level fixed effects (demographics omitted) with clustered standard errors by ZIP codes

Variable	Full	VMT_{it}^{Q1}	VMT_{it}^{Q2}	VMT_{it}^{Q3}	VMT_{it}^{Q4}	VMT_{it}^{Q5}
log(gasprice)	-0.117***	-0.172***	-0.103***	-0.0912***	-0.138***	-0.0576***
	(0.00758)	(0.0155)	(0.0181)	(0.0168)	(0.0168)	(0.018)
log(unemp)	0.277***	0.453***	0.231***	0.269***	0.213***	0.217***
	(0.00449)	(0.00969)	(0.0113)	(0.00968)	(0.00966)	(0.0101)
log(GDP)	4.77***	6.07***	4.24***	4.61***	4.4***	4.22***
	(0.0482)	(0.1)	(0.119)	(0.105)	(0.105)	(0.113)
log(age)	0.275***	0.39***	0.372***	0.253***	0.187***	0.159***
	(0.00226)	(0.00486)	(0.00513)	(0.00516)	(0.00504)	(0.00507)
Adj R Sq	0.706	0.682	0.739	0.707	0.698	0.703
n	5,832,311	1,392,518	1,045,377	1,182,301	1,145,652	1,066,211

In the regression results, we observe consistency in the coefficients of our control variables

[9]***: $p = .01$, **: $p = .05$, *: $p = .1$

such as unemployment and GDP, with the exception of Q1 of driving intensity in both cohorts. Despite the longitudinal robustness of the 2002 cohort, our general model consistently has better R-squared values for the 2006 cohort, suggesting that the elasticity estimates for the latter cohort may be more accurate (and they match ranges of elasticities in Figure 6.1).

6.4.2 Heterogeneity of gasoline price elasticity over ranges of gas prices

Our second approach examines the gasoline price elasticity with respect to driving intensity over different ranges of gas prices. Again, we observe non-uniform response at different levels of gasoline prices as seen in Table 6.6. When we control for levels of gas prices using dummy variables at different levels of fuel prices, we observe relatively uniform response except at the highest levels of gas prices in both cohorts. The price elasticity for gasoline ranges from -0.011 to -0.045 over ranges of fuel prices from $1 per gallon to $4 per gallon in the 2002 cohort. Similarly, the elasticities range from -0.0028 to -.05 over the same range in the 2006 cohort. These elasticities range in statistical significance, with most at the $p = 0.1$. However, at $4 per gallon, responsiveness drastically increases with a price elasticity of -0.209 and -0.182 in the two cohorts and are statistically significant at $p = 0.01$. The results indicate that driver response to price changes is relatively uniform across different levels of gas prices, but becomes very sensitive at the highest fuel prices: a 1% increase in fuel price below $4/gallon nets a reduction in overall driving by about 1-5% while a 1% increase in fuel price above $4/gallon nets a reduction in overall driving by approximately 20%.

The implications of such results indicate that there is a non-linear relationship between driving intensity and gasoline prices. Average gas price elasticities are likely adequate to measure responses at normal gas prices ranging from $1/gallon to $4/gallon but are probably incorrect at higher gas price levels. However, we caveat this inference on the fact that the response seen in the results from Table 6.6 are likely short-run elasticity measurements given the relatively abrupt period of time that gasoline prices were above $4/gallon. Consumers may have anticipated future drops in gasoline prices and decreased their driving intensity during the period of high fuel prices. It may be the case that long-run elasticities are not quite as high as those observed in our results.

Table 6.6: Regression results on log(VMT) with gas price interactions, and monthly and vehicle level fixed effects (demographics omitted) with clustered standard errors by ZIP codes

Variable	2002 Cohort	2006 Cohort
log(gas price)	-0.0387*	-0.0538**
	(0.0356)	(0.0225)
log(unemployment)	0.413***	0.303***
	(0.0237)	(0.0118)
log(GDP)	4.94***	4.24***
	(0.199)	(0.104)
log(age)	0.382***	0.275***
	(0.00756)	(0.00628)
log(gas price)*(gas \$1-\$2)	-	-
	-	-
log(gas price)*(gas \$2-\$3)	0.0282	0.051**
	(0.0362)	(0.021)
log(gas price)*(gas \$3-\$4)	-0.0061	0.026*
	(0.0345)	(0.0201)
log(gas price)*(gas >\$4)	-0.1703***	-0.128***
	(0.0389)	(0.0191)
Adj R Sq	0.665	0.706
n	1,570,866	5,832,307

6.5 Heterogeneity of gasoline price elasticity over ranges of fuel efficiencies

Our final examination of elasticity heterogeneity is over different ranges of vehicle fuel efficiencies. We measure responses over differing vehicle economies by both separating the data by quantiles of fuel economy and by interacting the fuel economies with gas prices. The results for the different approaches are not analogous as the quantile values (Table 6.3) differ from the categorical FE variable (described in Section 6.3.1).

The results of our fixed effects approach dividing data by quantiles of vehicle fuel economies can be seen in Table 6.7. The elasticities are negative and statistically significant, but are relatively uniform in the 2002 cohort (representing most of urban Pennsylvania). The fourth quantile of fuel economies have the highest elasticity value of -0.233 while the other quantiles have elasticities ranging from -0.0806 to -0.123. In this cohort, there appear to be slight differences in gas price elasticity values, though there is not a clear trend in changes across vehicle fuel economies.

Table 6.7: Regression results on log(VMT), 2002–2010 data separated by quantiles of FE with monthly and vehicle level fixed effects (demographics omitted) with clustered standard errors by ZIP codes

Variable	Full	FE_{it}^{Q1}	FE_{it}^{Q2}	FE_{it}^{Q3}	FE_{it}^{Q4}	FE_{it}^{Q5}
log(gasprice)	-0.131***	-0.0893**	-0.0806*	-0.114**	-0.223***	-0.123**
	(0.0182)	(0.0389)	(0.0458)	(0.0389)	(0.0387)	(0.0422)
log(unemp)	0.374***	0.56***	0.28***	0.432***	0.334***	0.238***
	(0.0136)	(0.0303)	(0.0361)	(0.0283)	(0.0277)	(0.0309)
log(GDP)	5.42***	5.79***	4.52***	5.45***	5.83***	5.03***
	(0.103)	(0.222)	(0.268)	(0.218)	(0.215)	(0.238)
log(age)	0.383***	0.488***	0.572***	0.371***	0.281***	0.232***
	(0.00385)	(0.00828)	(0.00993)	(0.00822)	(0.00816)	(0.00877)
Adj R Sq	0.665	0.618	0.696	0.659	0.664	0.677
n	1,570,869	342,191	269,862	331,121	331,580	295,671

The results for the 2006 cohort of vehicles in Table 6.8 (representing the majority vehicles in Pennsylvania) differ from those in the 2002 cohort (Table 6.7). We find that the most sensitive group of vehicles are those in the first quantile (representing the least fuel efficient vehicles) with an elasticity value of -0.172–a sensible result given that the marginal cost of driving is highest for these vehicles. With the exception of the fourth quantile of data, we find that gas price elasticity consistently decreases as the fuel economy of the vehicle increases. The intuition behind this trend is that change in price of gasoline is not a uniform price change effect to consumers since the cost of driving is also a function of the fuel economy of the vehicle. As is expected, the price changes have a smaller effect on vehicles with higher fuel economy values as the marginal change in the cost of driving is relatively smaller for changes in gasoline prices compared to vehicles with lower fuel economy values.

Table 6.8: Regression results on log(VMT), 2006–2010 data separated by quantiles of FE with monthly and vehicle level fixed effects (demographics omitted) with clustered standard errors by ZIP codes

Variable	Full	FE_{it}^{Q1}	FE_{it}^{Q2}	FE_{it}^{Q3}	FE_{it}^{Q4}	FE_{it}^{Q5}
log(gasprice)	-0.117***	-0.172***	-0.103***	-0.0912***	-0.138***	-0.0576***
	(0.00758)	(0.0155)	(0.0181)	(0.0168)	(0.0168)	(0.018)
log(unemp)	0.277***	0.453***	0.231***	0.269***	0.213***	0.217***
	(0.00449)	(0.00969)	(0.0113)	(0.00968)	(0.00966)	(0.0101)
log(GDP)	4.77***	6.07***	4.24***	4.61***	4.4***	4.22***
	(0.0482)	(0.1)	(0.119)	(0.105)	(0.105)	(0.113)
log(age)	0.275***	0.39***	0.372***	0.253***	0.187***	0.159***
	(0.00226)	(0.00486)	(0.00513)	(0.00516)	(0.00504)	(0.00507)
Adj R Sq	0.706	0.682	0.739	0.707	0.698	0.703
n	5,832,311	1,392,518	1,045,377	1,182,301	1,145,652	1,066,211

Our findings in the interaction of categories of fuel economies and gas prices approach (Table 6.9) are consistent with the results from regressing on quantiles of fuel economy for the 2006 cohort (Table 6.8). For vehicles below 20 MPG, the elasticities are the lowest among all fuel economy categories with values of -0.215 and -0.173 for the 2002 and 2006 cohorts respectively. As the vehicle fuel economies increase, we find a similar trend with a decrease in the response to gasoline price changes in both cohorts, at the highest fuel economy category of vehicles greater than 40 MPG the elasticity values are slightly positive but no longer statistically significant.

Our findings have important implications for the rebound effect. Since drivers of more fuel efficient vehicles are less responsive than other drivers, the gains from policy pushes towards high fuel efficient vehicles are likely to be offset to a degree by the fact that responsiveness to price signals from changing gas prices will be decreased on average.

6.6 Conclusions

In contrast to many economic studies measuring the average price elasticity of gasoline with respect to driving behavior, our approach focuses on understanding how different factors affect the elasticity. The heterogeneity of gas price elasticities has important policy implica-

Table 6.9: Regression results on log(VMT) with fuel economy interactions, and monthly and vehicle level fixed effects (demographics omitted) with clustered standard errors by ZIP codes

Variable	2002 Cohort	2006 Cohort
log(gas price)	0.0689	-0.046**
	(0.0983)	(0.016)
log(unemployment)	0.374***	0.277***
	(0.0237)	(0.012)
log(GDP)	5.38***	4.75***
	(0.182)	(0.0971)
log(age)	0.384***	0.275***
	(0.00761)	(0.00625)
log(gas price)*(FE <20mpg)	-0.284***	-0.127***
	(0.0909)	(0.00718)
log(gas price)*(FE 20-30mpg)	-0.169*	-0.0495***
	(0.0908)	(0.00622)
log(gas price)*(FE 30-40mpg)	-0.08	-
	(0.0913)	-
log(gas price)*(FE >40mpg)	-	0.0146
	-	(0.0461)
Adj R Sq	0.665	0.706
n	1,570,866	5,832,308

tions: both in understanding how broadly applied regulation may affect different segments of the population as well as to help policy-makers generate more efficient strategies that affect driving behavior.

Differences in elasticity over driving intensities provide some insight on how changing the cost of driving may affect the population of drivers in a non-uniform manner. Specifically, our findings that higher driving intensity corresponds to lower responsiveness to price signals indicates that policies that raise the cost of driving will disproportionately affect the portion of the population with the lowest driving intensity. The flexibility afforded to individuals who drive the least number of annual miles likely makes them the most sensitive to policies that affect the cost of driving. Our work points out that behavioral response will not be equally distributed across the population but will have higher impact on those with the lowest driving intensities. Heterogeneity of elasticity across gasoline price levels has important implications for consumer responsiveness to policies affecting prices of gasoline, such as gas taxes. Our results indicate that the elasticity is relatively uniform below prices of \$4/gallon (with values ranging from -0.002 to -0.05), but is magnified to -0.182 at prices above \$4/gallon. The large increase in elasticity indicates a drastically different response to the implementation of a flat fuel tax that would be dependent on the current level of gasoline prices. Our work indicates that average price elasticities would likely underestimate the effects of a tax regime at higher fuel prices. If the purpose of such tax is to achieve some decrease in overall vehicle miles travelled in the US through behavioral response to price signals, the fee ought to be dependent on fuel price levels in order to achieve uniform responsiveness across different fuel prices (e.g. a flat tax that decreases if fuel prices rise above \$4/gal).

Our final investigation of elasticity variation is across vehicle fuel economies. The common trend found in our results reveals that the response to changes in gas prices diminishes as the fuel economy of the vehicle increases. This finding corresponds with our intuition since changes to the cost of driving are a function of both fuel prices and the efficiency of the vehicle. However, the decrease in responsiveness is important to understand in the context of policies such as the Corporate Average Fuel Economy (CAFE) standards, which increases fuel economy of vehicles in the US fleet. Capturing the heterogeneity of elasticities across fuel economies is particularly important in regards to policies such as CAFE, as gauging the effects of such a policy on driving behavior with average gas price elasticity values fails to differentiate behavioral changes that are a direct result of the policy.

This study sheds some light on estimates of elasticity of driving behavior in response to changes in gasoline prices, specifically focusing on the heterogeneity of the values over levels of gas prices, driving intensity, and vehicle fuel economies. While the quantitative estimates are sensibly within the range of elasticity values in the existing literature, more significantly the variation of elasticities and trends described by our findings are critically important in the context of understanding the effects of policies such as gasoline taxes or CAFE standards. Future work can extend our examination of heterogeneity to other factors as well as to compare quantitative estimates using data outside of Pennsylvania to determine whether our results are localized within the state or can be broadly applied elsewhere.

Chapter 7

Conclusion

There is tremendous potential for transportation policy to assist in a transition towards a more fuel efficient fleet as well as to promote the widespread adoption of alternative fuel vehicles. The transformation of the transportation system can provide long-lasting benefits to US energy security and worldwide climate change mitigation. However, my work points out some of the complexities and difficulties of implementing effective policies. It is difficult to measure the effects of a policy to demonstrate whether its stated goals are met. But even if policy functions well on its own, unintentional inefficiencies may arise when interacting with other policies. In addition, side-effects of successful policies may be overlooked, resulting in diminished or even negative gains. The results of my study provide some insights into these policy effects and potential suggestions for future improvement of the policies.

7.1 Summary of Results and Recommendations

In Chapter 2, I find that the effect of EPACT tax credit incentives are typically overestimated, but do provide a boost in the sales of hybrid electric vehicles by as much as 15%. This indicates that the use of monetary credits can be employed as a method of incentivizing the adoption of alternative fuel vehicles in the future. One interesting finding is that the incentives are only effective at quantities above $1,000 indicating that spreading out small monetary incentives is less effective than focusing an incentive program with higher credit amounts. However, further study on the effectiveness of incentives for vehicles with relatively different attributes than traditional ICVs is needed as it may be the case that a greater monetary amount is required to incentive a consumer to switch to an alternative fuel vehicle (due to limitations such as electric range for EVs). To this end, BEVs and PHEVs have now been on the market for several years and there have been enough policy incentive shifts that would provide adequate data to study.

I investigate the implications of electric vehicle adoption on transportation infrastructure revenue in Chapter 3. While the revenue decrease is measurable (I find a $200 million cumulative decrease by 2025), the quantity is essentially negligible compared to the total cash flows for transportation infrastructure. However, transportation departments in the US ought to consider alternative revenue generation possibilities since the adoption of alternative fuel vehicles can present difficulties for funding infrastructure in the long-term. I propose some methods of revenue generation for policy consideration: use fees that can be charged based on odometer readings of vehicles during inspections, use fees based on the charging of electric vehicles, or altering annual registration fees to be a function of a vehicle's MSRP. The implementation of these fees are likely politically contentious, but some consideration of the issue is necessary to avoid reductions in future revenues for transportation infrastructure.

Chapters 4 and 5 demonstrate severe inefficiencies in the CAFE and ZEV policies. The AFV incentives in CAFE essentially adds the emissions of a midsize vehicle onto the road for every AFV sold. When paired in conjunction with the ZEV mandates, short-term emissions for new vehicles through 2025 increases by a cumulative 120 million tons of CO_2, more than 10% of the expected emissions savings from the implementation of the new CAFE standards in 2012. While the emissions penalty may be offset by long-term reductions due to high penetration of AFVs in the market, the inefficiencies from the policy interactions may be entirely avoidable with better structured policy. With the upcoming evaluations of CAFE and ZEV in 2015, my work provides insights on some unintentional consequences of current policy implementation and can provide guidance on some of the shortcomings described in Chapters 4 and 5.

Finally, my work in Chapter 6 reveals the importance of heterogeneity in the elasticity of driving behavior with respect to gasoline prices. While the elasticity is commonly estimated as an average response across all individuals, I demonstrate that the response can vary quite dramatically over a number of factors. For example, I find a continuous decrease in responsiveness as driving intensity increases while the elasticity stays relatively small for low gas prices but is large for gas prices above $4. For policymakers to properly estimate the effects of policies that change the cost of driving on driving behavior, a more detailed measure of elasticity is needed. My work only investigates three factors that affect the elasticity, but further work can be performed on investigating the heterogeneity over other factors.

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Chapter 8

Appendix

8.1 Appendix A2: Chapter 2 Supplemental Information

Table 8.1: Energy Polic Act of 2005, HEV Tax Credit

Toyota	Jan 1-Sep 30, 2006	Oct 1, 2006-Mar 31, 2007	Apr 1-Sep 30, 2007
2005 Prius	$3,150.00	$1,575.00	$787.50
2006 Prius	$3,150.00	$1,575.00	$787.50
2006 Highlander	$2,600.00	$1,300.00	$650.00
2006 Lexus RX400h	$2,200.00	$1,100.00	$550.00
2007 Prius	$3,150.00	$1,575.00	$787.50
2007 Highlander	$2,600.00	$1,300.00	$650.00
2007 Lexus RX400h	$2,200.00	$1,100.00	$550.00
2007 Camry Hybrid	$2,600.00	$1,300.00	$650.00
2007 Lexus GS 450h	$1,550.00	$775.00	$387.50
2008 Prius	$3,150.00	$1,575.00	$787.50
2008 Highlander	$2,600.00	$1,300.00	$650.00
2008 Lexus RX400h	$2,200.00	$1,100.00	$550.00
2008 Camry Hybrid	$2,600.00	$1,300.00	$650.00
2008 Lexus LS 600h			$450.00
Honda	Jan 1, 2006-Dec 31, 2007	Jan 1-Jun 30, 2008	July 1-Dec 31, 2008
2005 Insight	$1,450.00	$725.00	$362.50
2005 Accord	$650.00	$325.00	$162.50
2005 Civic	$1,700.00	$850.00	$425.00
2006 Insight	$1,450.00	$725.00	$362.50
2006 Accord	$650.00	$325.00	$162.50
2006 Accord (control calib)	$1,300.00	$650.00	$325.00
2006 Civic	$2,100.00	$1,050.00	$525.00
2007 Accord	$1,300.00	$650.00	$325.00
2007 Civic	$2,100.00	$1,050.00	$525.00
2008 Civic	$2,100.00	$1,050.00	$525.00
2009 Civic	$2,100.00	$1,050.00	$525.00
Ford	Jan 1, 2006-Mar 31, 2009	Apr 1-Sep 30, 2009	Oct 1, 2009-Mar 31, 2010
2005 Escape 2WD	$2,600.00	$1,300.00	$650.00

2005 Escape 4WD	$1,950.00	$975.00	$487.50
2006 Escape 2WD	$2,600.00	$1,300.00	$650.00
2006 Escape 4WD	$1,950.00	$975.00	$487.50
2007 Escape 2WD	$2,600.00	$1,300.00	$650.00
2007 Escape 4WD	$1,950.00	$975.00	$487.50
2006 Mercury Mariner	$1,950.00	$975.00	$487.50
2007 Mercury Mariner	$1,950.00	$975.00	$487.50
2008 Escape 2WD	$3,000.00	$1,500.00	$750.00
2008 Escape 4WD	$2,200.00	$1,100.00	$550.00
2008 Mercury Mariner 2WD	$3,000.00	$1,500.00	$750.00
2008 Mercury Mariner 4WD	$2,200.00	$1,100.00	$550.00
2009 Escape 2WD	$3,000.00	$1,500.00	$750.00
2009 Escape 4WD	$1,950.00	$975.00	$487.50
2009 Mercury Mariner 2WD	$3,000.00	$1,500.00	$750.00
2009 Mercury Mariner 4WD	$1,950.00	$975.00	$487.50
2010 Escape 2WD	$3,000.00	$1,500.00	$750.00
2010 Escape 4WD	$2,600.00	$1,300.00	$650.00
2010 Fusion	$3,400.00	$1,700.00	$850.00
2010 Mercury Mariner 2WD	$3,000.00	$1,500.00	$750.00
2010 Mercury Mariner 4WD	$2,600.00	$1,300.00	$650.00
2010 Mercury Milan	$3,400.00	$1,700.00	$850.00
Porsche	1-Jan-06		
2011 Cayenne S	$1,800.00		
Mercedes-Benz	1-Jan-06		
2010 ML 450	$2,200.00		
2010 S400	$1,150.00		
2011 ML 450	$2,200.00		
Chrysler/Dodge	1-Jan-06		
2009 Chrysler Aspen	$2,200.00		
2009 Dodge Durango	$2,200.00		
GMC	1-Jan-06		
2006 Chevrolet Silverado 2WD	$250.00		
2006 Chevrolet Silverado 4WD	$650.00		
2006 GMC Sierra 2WD	$250.00		
2006 GMC Sierra 4WD	$650.00		
2007 Chevrolet Silverado 2WD	$250.00		
2007 Chevrolet Silverado 4WD	$650.00		
2007 GMC Sierra 2WD	$250.00		
2007 GMC Sierra 4WD	$650.00		
2007 Saturn Aura	$1,300.00		
2007 Saturn Vue	$650.00		
2008 Chevrolet Malibu	$1,300.00		
2008 Chevrolet Tahoe	$2,200.00		
2008 GMC Yukon	$2,200.00		
2008 Saturn Aura	$1,300.00		
2008 Saturn Vue	$1,550.00		
2009 Cadillac Escalade 2WD	$2,200.00		
2009 Cadillac Escalade AWD	$1,800.00		
2009 Chevrolet Malibu	$1,550.00		
2009 Chevrolet Silverado	$2,200.00		
2009 Chevrolet Tahoe	$2,200.00		
2009 GMC Sierra	$2,200.00		
2009 GMC Yukon	$2,200.00		
2009 Saturn Aura	$1,550.00		
2009 Saturn Vue	$1,550.00		
2010 Cadillac Escalade	$2,200.00		
2010 Chevrolet Silverado	$2,200.00		
2010 Chevrolet Tahoe	$2,200.00		
2010 GMC Sierra	$2,200.00		
2010 GMC Yukon	$2,200.00		
2011 Cadillac Escalade	$2,200.00		
2011 Chevrolet Silverado	$2,200.00		
2011 Chevrolet Tahoe	$2,200.00		
2011 GMC Sierra	$2,200.00		
2011 GMC Yukon	$2,200.00		

Mazda	1-Jan-06
2008 Tribute 2WD	$3,000.00
2008 Tribute 4WD	$2,200.00
2009 Tribute 2WD	$3,000.00
2009 Tribute 4WD	$1,950.00
Nissan	1-Jan-06
2007 Altima	$2,350.00
2008 Alitma	$2,350.00
2009 Altima	$2,350.00
2010 Altima	$2,350.00
2011 Altima	$2,350.00
BMW	1-Jan-06
2010 ActiveHybrid X6	$1,550.00
2011 ActiveHybrid 750i	$900.00
2011 ActiveHybrid X6	$1,550.00

Table 8.2 displays results from fixed effects models without accounting for natural growth, and using time dummies for every month under the period of the analysis (not listed).

$$\ln(S_{it}) = \alpha + \beta(\mathrm{EPACT}_{it}) + \gamma(x_{it}) + u_i + \varepsilon_{it} \tag{8.1}$$

Table 8.2: Summary fixed-effects regression results

Variables	lnsales
taxrelief	-0.422
	-0.791
taxreliefnh	-0.0982
	-0.104
cashforclunkers	-4.443***
	-0.723
import	0.967***
	-0.107
prodstop	-5.706***
	-0.147
priusad	0.976***
	-0.225
lnunemp	-1.208***
	-0.208
lnunemph	1.370**
	-0.565
lngas6	-1.756***
	-0.244
lngas6h	4.553***
	-1.487
epact	**0.000311***
	-0.00016
L.lnsales	
L.lnsalesh	
Constant	8.891***
	-0.377
Observations	23,843
R-squared	0.654
Number of Groups	428

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

8.2 Appendix A3: Chapter 3 Supplemental Information

Table 8.3: Breakdown of Vehicle Fees by State

State	Sales Tax	State Fuel Tax (¢/gallon)	Title Fees	Registration Fees	Inspection Fees
Alabama	4.00%	20.9	$15.00	$23 Annually	1 time inspection, free of charge; safety
Alaska	0.00%	8	$15.00	$100 Biannually	No inspections
Arizona	6.60%	19	$4.00	$9.50 Annually plus vehicle license tax of 2.8% (assessed value of 60% of the MSRP - reduced by 16.25% each year)	$20, biannually; emissions
Arkansas	6.00%	21.8	$5.00	Annually: $17/car 3,000 lbs. or less, $25/car 3,000 lbs. - 4,500 lbs., $30/car over 4,500 lbs., $2.50 validation decal for all automobiles.	No inspections
California	6.25%	50.5	$18.00	$46 Annually, plus additional fees based on vehicle type, license plate type, county of residence, and driving record	$20 for first 6 years, afterwards $8.25 + $12 biannually; emissions
Colorado	2.90%	22	$9.05	Declining annual fee based on percentage of MSRP with a flat fee of $73 after 10 years	$10 vin inspection 1 time inspection, $25 annually emissions test
Connecticut	6.35%	45	$25.00	$40 Annually	$10 vin inspection 1 time inspection, $20 biannually; emissions
Delaware	0.00%	23	$35.00	$40 Annually	Emissions testing is free
Florida	6.00%	35	$77.25	$225 - initial registration plus Annually: $19.50- vehicle under 2,500 lbs., $30.50 - vehicle between 2,500 lbs. - 3,499 lbs., $44.00 - vehicle over 3,500 lbs.	No inspections
Georgia	4.00%	28.6	$18.00	$20 Annually	Exempt first two years, $10-$25 annually afterwards; emissions
Hawaii	4.00%	48.8	$5.00	Annually: $45 plus $0.0075 per pound for vehicles <4,000 lbs., $0.01 per pound for vehicles 4,000 to 7,000 lbs., $0.0125 per pound for vehicles >7,000 lbs.	Exempt first two years, $15 annually afterwards; safety

Idaho	6.00%	25	$14.00	Annually: $48 for vehicles 1-2 years old, $36 for vehicles 3-6 years old, $24 for vehicles 7 or more years old	$11 biannually; emissions
Illinois	6.25%	42.5	$95.00	$99 Annually	Exempt first four years, $20 biannually; emissions
Indiana	7.00%	41.2	$15.00	$21.05 Annually	Emissions testing is free
Iowa	6.00%	22	$25.00	Registration fees for vehicles up to 11 years old are $0.40 per 100 lbs. plus a percentage of the vehicle's value: vehicles up to 7 years old - 1%, vehicles 8-9 years old - .75%, vehicles up to 10-11 years old - .5%, For vehicles 12 years old and older registration fee is $50	No inspections
Kansas	6.30%	25	$10.00	Annually: $35/car less than 4500 lbs., $45/car over 4500 lbs.	$20 1 time inspection; vin
Kentucky	6.00%	29.9	$10.00	$21 Annually	No inspections
Louisiana	4.00%	20	$18.50	Rate is 0.1% of vehicle price with a minimum base of $10,000; License plates sold every two years. An $8.00 handling fee added to all transactions	Annually, $10-$18 depending on location; emissions
Maine	5.00%	31.5	$33.00	$35 Annually	$18.50 annually; safety and emissions
Maryland	6.00%	23.5	$100.00	Annually: $128/car less than 3700 lbs., $180/car over 3700 lbs.	Exempt first two years, $14 annually afterwards; emissions
Massachusetts	6.25%	23.5	$75.00	$50 biannually	$29 annually; emissions and safety
Michigan	6.00%	42.1	$15.00	Fees depend on the price of the vehicle; vary from $33 to $148 and decline by 10% each year until the fifth renewal.	No inspections
Minnesota	6.88%	28.6	$13.75	Registration tax system for passenger vehicles based on value of vehicle	No inspections
Mississippi	7.00%	18.8	$9.00	$14 Annually	$5 annually; safety
Missouri	4.23%	17.3	$11.00	Less than 12 horsepower (hp) - $18.50, 12 hp - 23 hp: $21.25, 24 hp - 35 hp : $24.25, 36 hp - 47 hp: $33.25, 48 hp - 59 hp: $39.25, 60 hp - 71 hp: $45.25, 72 hp and greater: $51.25; $3.50 processing fee	$12 safety inspection biannually, $24 emissions inspection biannually
Montana	0.00%	27.8	$12.00	Under 4 yrs. old $217.00, 5 10 yrs. old $87.00, 11+ yrs. old $28.00	No inspections
Nebraska	5.50%	27.1	$10.00	$15 Annually	$10 1 time inspection; safety
Nevada	6.85%	33.1	$28.25	$33 Annually	$39.5 to $50 annually; emissions
New Hampshire	0.00%	19.6	$25.00	0-3000 lbs. $31.20, 3001-5000 lbs. $43.20, 5001-8000 lbs. $55.20, 8001-73,280 lbs. $ .96 per hundred lbs. gross weight	$20-$50 annually; emissions and safety

New Jersey	7.00%	14.5	$60.00	2 years or younger: $59 <3,500 lbs., $84 >3,500 lbs.; Older than 2 years: $46.50 <3,500 lbs., $71.50 >3,500 lbs.	Emissions testing is free
New Mexico	5.13%	18.9	$3.00	Varies by year and weight of vehicle	$15-$20 biannually; emissions
New York	4.00%	51.3	$55.00	Fee ≈ .02*weight-12	$10 safety inspection annually, $27 emissions inspection annually
North Carolina	4.75%	37.8	$40.00	$28 Annually	$30 emissions inspection annually, $13.6 safety inspection annually
North Dakota	5.00%	23	$5.00	Varies by year and weight of vehicle	No inspections
Ohio	5.50%	28	$16.00	$34.50 Annually	Emissions testing is free
Oklahoma	4.50%	17	$11.00	$91 1st- 4thyears of registration, $81 5th-8thyears of registration, $61 9th-12thyears of registration, $41 13th-16thyears of registration, $21 17th+ years of registration; All vehicles subject to an additional $5 in other fees	No inspections
Oregon	0.00%	31	$77.00	$86 bianually	$7 1 time VIN inspection, $19 emissions inspection biannually
Pennsylvania	6.00%	32.3	$22.50	$36 Annually	$35-$50 emissions inspection annually, $16-$20 safety inspections annually
Rhode Island	7.00%	33	$51.50	Varies by weight of vehicle	$39 bianually
South Carolina	6.00%	16.8	$15.00	$24 Annually	No inspections
South Dakota	4.00%	24	$5.00	Fee depends on weight and age	No inspections
Tennessee	7.00%	21.4	$13.00	$24 Annually	$10 annually; emissions
Texas	6.25%	20	$13.00	$50.75 <6000 lbs., $54 >6000 lbs.	$14.25-$27.25 annually; emissions and safety
Utah	4.70%	24.5	$6.00	$43 Annually	$17 every 4 years until 10 years old, annually afterwards for safety, $28 every 2 years until 6 years old, annually afterwards for emissions
Vermont	6.00%	26.5	$33.00	Annually: $77 gas, $27 diesel, $122 other	$5 annually; safety
Virginia	4.00%	20.1	$10.00	$40.75 <4000 lbs., $45.75 >4000 lbs.	$16 safety inspection annually; $28 emissions inspection biannually
Washington	6.50%	37.5	$25.50	$43.75: 0 4k lbs., $53.75: 4,001 6,000 lbs., $63.75: 6,001 8,000 lbs.	$7.50 annually; emissions
West Virginia	6.00%	33.4	$10.00	$30 Annually	$12.36 annually; safety
Wisconsin	5.00%	32.9	$69.50	$75 Annually	Emissions testing is free

Wyoming	4.00%	14	$9.00	$15 (plus county registration that is calculated by a percentage of factory price of the vehicle and the age of the vehicle)	$9 1 time VIN inspection

8.3 Appendix A4: Chapter 4 Supplemental Information

8.3.1 Footprint-based standard calculations

Equation (4.1) is a simplification of the actual emission rate standards, in order to accommodate the actual footprint standards the equation is modified as seen below in Equation (8.2).

$$\frac{\sum_{j_f} n_{j_f} \left(s_{j_f} = \begin{cases} a \text{ if } f \leq g \\ cf + d \text{ if } g < f \leq h \\ b \text{ if } f > h \end{cases} \right)}{N} = \frac{\sum_{j_f} n_{j_f} r_{j_f}}{N} \tag{8.2}$$

s on the left-hand side of the equation is not a fixed value and is actually constructed from a piecewise function dependent on the footprint of the vehicle f, with parameters $g = 41$ and $h = 56$ for passenger vehicles and $g = 41$ and $h = 66$ for light-duty trucks. The $abcd$ parameters can be found below in Tables 8.4-8.7.

Table 8.4: abcd Coefficients for Passenger Vehicle Footprint Calculation, 2012-2016 Rule

Coefficient	2012	2013	2014	2015	2016
a	244	237	228	217	206
b	315	307	299	288	277
c	4.72	4.72	4.72	4.72	4.72
d	50.5	43.3	34.8	23.4	12.7

Table 8.5: abcd Coefficients for Passenger Vehicle Footprint Calculation, 2017-2025 Rule

Coefficient	2017	2018	2019	2020	2021	2022	2023	2024	2025
a	194.7	184.9	175.3	166.1	157.2	150.2	143.3	136.8	130.5
b	262.7	250.1	238	226.2	214.9	205.5	196.5	187.8	179.5
c	4.53	4.35	4.17	4.01	3.84	3.69	3.54	3.4	3.26
d	8.9	6.5	4.2	1.9	-0.4	-1.1	-1.8	-2.5	-3.2

Table 8.6: abcd Coefficients for Light-duty Truck Footprint Calculation

Coefficients	2012	2013	2014	2015	2016
a	294	284	275	261	247
b	395	385	376	362	348
c	4.04	4.04	4.04	4.04	4.04
d	128.6	118.7	109.4	95.1	81.1

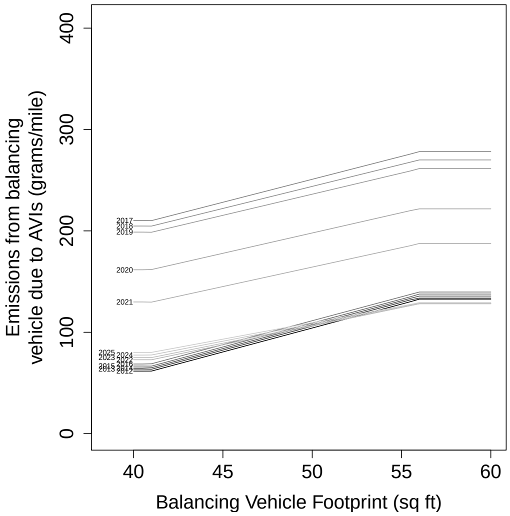
Table 8.7: abcd Coefficients for Light-duty Truck Footprint Calculation

Coefficients	2017	2018	2019	2020	2021	2022	2023	2024	2025
a	238.1	226.8	219.5	211.9	195.4	185.7	176.4	167.6	159.1
b	347.2	341.7	338.6	336.7	334.8	320.8	305.6	291	277.1
c	4.87	4.76	4.68	4.57	4.28	4.09	3.91	3.74	3.58
d	38.3	31.6	27.7	24.6	19.8	17.8	16	14.2	12.5
a′	246.4	240.9	237.8	235.9	234	234	234	234	234
b′	347.4	341.9	338.8	336.9	335	335	335	335	335
c′	4.04	4.04	4.04	4.04	4.04	4.04	4.04	4.04	4.04
d′	80.5	75	71.9	70	68.1	68.1	68.1	68.1	68.1

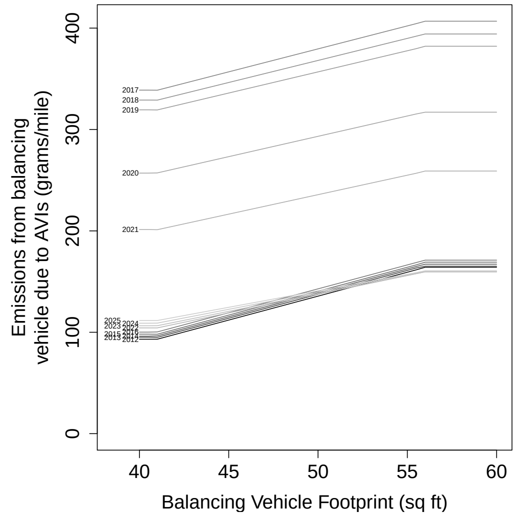
Note that the second set of coefficients in Table 8.7 determines a second piecewise linear curve. The emissions rate requirement is equal to the minimum between the two piecewise curves for light-duty trucks in 2017 to 2025.

Likewise to Equation (8.2), we extend the piecewise linear footprint functions to Equation (4.2) which incorporates AVIs in a general framework below in Equation (8.3).

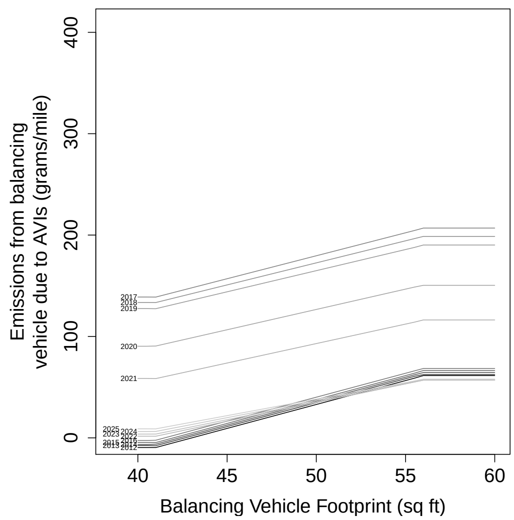
$$\frac{\sum_{j_f} n_{j_f}\left(s_{j_f} = \begin{cases} a \text{ if } f \leq g \\ cf + d \text{ if } g < f \leq h \\ b \text{ if } f > h \end{cases}\right)}{N} = \frac{\sum_{j_f \in C} n_{j_f} r_{j_f} + \sum_{j_f \in A} \left(w_{j_f} p_{j_f} r^{\mathrm{A}}_{j_f} + \left(1 - p_{j_f}\right) r^{\mathrm{G}}_{j_f}\right) n_{j_f}}{\sum_{j_f \in C} n_{j_f} + \sum_{j_f \in A} n_{j_f} m_{j_f}} \tag{8.3}$$



(a) Balancing to a Chevy Volt (PHEV)

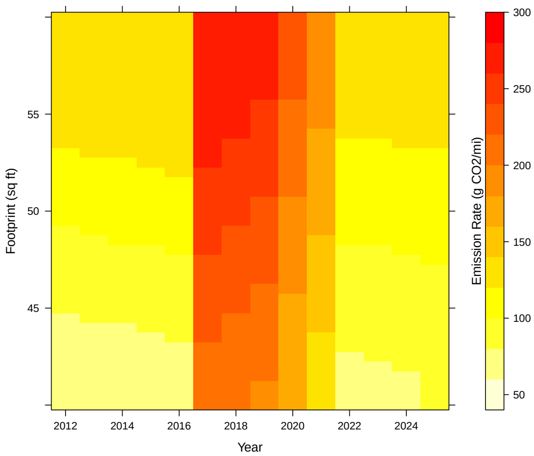


(b) Balancing to a Nissan Leaf (BEV)

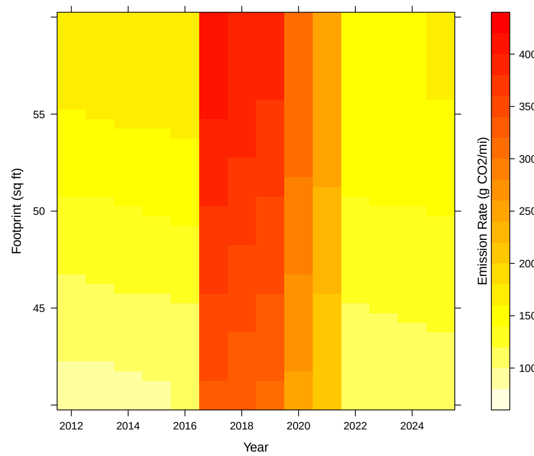


(c) Balancing to a Toyota Prius (PHEV)

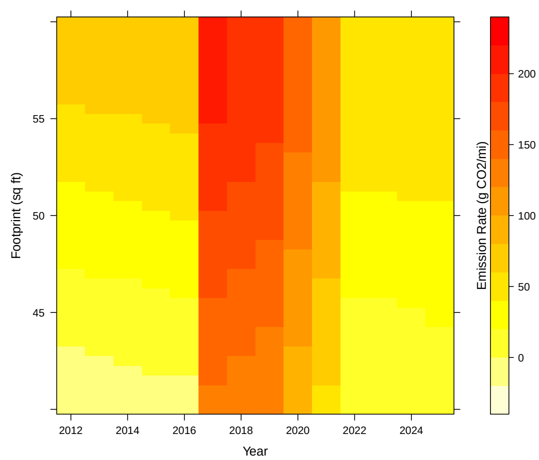
Figure 8.1: Incremental emissions rate increase from car 2 with variable footprints balancing to various vehicle models



(a) Balancing to a Chevy Volt (PHEV)



(b) Balancing to a Nissan Leaf (BEV)



(c) Balancing to a Toyota Prius (PHEV)

Figure 8.2: Incremental emissions rate increase from car 2 with variable footprints balancing to various vehicle models

8.3.2 Balancing to an AFV to multiple different vehicles

Here we demonstrate that balancing to multiple different vehicle models n_i with emissions s_i rather than a single type of vehicle n_2 with emissions s_2 as in Equation (4.7) yields the same overall results. We repeat Equations (4.3)-(4.7) with this general case:

Emissions rate for AFV balancing vehicles r_i without CAFE AFV Incentives:

$$\frac{n_1 s_1 + \sum_{i=2}^{I} n_i s_i + \sum_{j=I+1}^{J} n_j s_j}{N} = \frac{n_1 \left(p_1 r_1^{\mathrm{A}} + (1-p_1)\, r_1^{G}\right) + \sum_{i=2}^{I} n_i r_i + \sum_{j=I+1}^{J} n_j r_j}{N} \tag{8.4}$$

where $N = \sum_{j=1}^{J} n_j$. Since $\bar{s} = \dfrac{\sum_{j=1}^{J} n_j s_j}{N}$ and $\bar{r} = \dfrac{\sum_{i=2}^{I} n_i s_i}{\sum_{i=2}^{I} n_i}$.

$$\therefore \bar{r}_i = \frac{N\bar{s} - \sum_{j=I+1}^{J} n_j r_j - n_1 \left(s_1 - \left(p_1 r_1^{\mathrm{A}} + (1-p_1)\, r_1^{\mathrm{G}}\right)\right)}{\sum_{i=2}^{I} n_i} \tag{8.5}$$

Emissions rate for AFV balancing vehicles r_i' with CAFE AFV Incentives:

$$\frac{n_1 s_1 + \sum_{i=2}^{I} n_i s_i + \sum_{j=I+1}^{J} n_j s_j}{N} = \frac{n_1 \left(w_1 p_1 r_1^{\mathrm{A}} + (1-p_1)\, r_1^{\mathrm{G}}\right) + \sum_{i=2}^{I} n_i r_i' + \sum_{j=I+1}^{J} n_j r_j}{N + n_1 (m_1 - 1)} \tag{8.6}$$

$$\therefore \bar{r}_i' = \frac{N\bar{s} - \sum_{j=I+1}^{J} n_j r_j - \bar{s} n_1 (m_1 - 1) + n_1 \left(s_1 - \left(w_1 p_1 r_1^{\mathrm{A}} + (1-p_1)\, r_1^{\mathrm{G}}\right)\right)}{\sum_{i=2}^{I} n_i} \tag{8.7}$$

Increase in balancing vehicle emissions rate due to CAFE AFV Incentives:

$$\Delta \bar{r}_i = \bar{r}_i' - \bar{r}_i = \frac{\bar{s} n_1 (m_1 - 1) + n_1 (1 - w_1)\, p_1 r_1^{\mathrm{A}}}{\sum_{i=2}^{I} n_i} \tag{8.8}$$

Note that the average increase in emissions $\Delta\bar{r}_i$ is equivalent to the increase seen in Equation (4.7).

8.4 Appendix A6: Chapter 6 Supplemental Information

8.4.1 Additional summary statistics

Table 8.8: Summary Statistics by Year (Mean and Std Dev)

	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Annual VMT	11,500	12,500	11,700	11,100	11,100	11,500	10,900	10,600	10,400	10,000	10,100
	15,000	11,600	9,890	9,600	9,640	10,500	9,090	8,780	8,680	8,550	8,280
Odometer	89,100	70,400	71,500	72,500	74,900	74,400	78,200	80,100	81,900	83,300	85,800
	52,700	48,200	43,400	44,300	45,200	46,000	47,400	48,400	49,100	50,000	50,600
Avg Gas Price	1.58	1.57	1.44	1.57	1.75	2.09	2.51	2.67	3.16	2.71	2.7
	0.05	0.06	0.04	0.06	0.11	0.17	0.17	0.11	0.26	0.3	0.13
Vehicle Age	8.15	6.56	7.23	7.53	7.77	7.71	8.08	8.35	8.62	8.92	9.19
	3.78	3.84	3.57	3.77	3.91	4.04	4.15	4.29	4.42	4.6	4.63
Fuel Efficiency (MPG)	23.9	23.3	23.3	23.2	23.1	23	22.9	22.9	22.9	22.9	22.9
	5.13	4.91	4.84	4.83	4.83	4.86	4.93	5.02	5.12	5.17	5.17
Unemployment (adj)	4.2	4.59	5.28	5.67	5.56	5.23	4.8	4.43	4.74	6.58	8.05
	0.08	0.23	0.24	0.1	0.09	0.15	0.15	0.13	0.29	0.85	0.66
GDP	12,600	12,700	12,800	13,000	13,500	14,000	14,400	14,700	14,900	14,600	14,600
	87.7	26.9	66.7	118	181	179	168	139	118	143	108

8.4.2 Quantile data summary statistics

Table 8.9: Summary Statistics by Annual VMT Quantile (Mean and Std Dev)

	VMT Q1	VMT Q2	VMT Q3	VMT Q4	VMT Q5
Annual VMT	3,750 2,590	7,300 3,380	9,830 4,110	12,700 5,290	18,600 14,500
Odometer	61,000 39,600	73,200 39,700	80,300 40,700	88,400 43,400	105,000 53,800
Avg Gas Price	2.3 0.561	2.3 0.565	2.31 0.567	2.32 0.564	2.32 0.557
Fuel Efficiency (MPG)	23.5 4.71	23.2 4.82	22.9 4.86	22.7 4.92	22.4 4.99
Unemployment (adj)	5.49 1.05	5.47 1.04	5.47 1.06	5.46 1.06	5.43 1.03
GDP	14,100 698	14,100 699	14,100 696	14,100 687	14,100 676

Table 8.10: Summary Statistics by Gas Price Quantile (Mean and Std Dev)

	Gas Q1	Gas Q2	Gas Q3	Gas Q4	Gas Q5
Annual VMT	10,700 9,520	9,130 7,750	10,500 8,200	11,400 7790	12,900 11,100
Odometer	91,200 46,800	82,100 45,000	72,000 43,500	73,200 43,700	90,000 47,900
Avg Gas Price	1.99 0.493	2.28 0.578	2.49 0.491	2.7 0.374	2.85 0.521
Fuel Efficiency (MPG)	23.2 4.79	23 4.86	22.8 4.92	22.6 4.99	22.8 4.8
Unemployment (adj)	5.28 0.583	5.49 1.03	5.53 1.21	5.62 1.41	5.46 1.27
GDP	13,700 700	14,000 723	14,300 521	14,600 287	14,600 316

Table 8.11: Summary Statistics by Fuel Efficiency Quantile (Mean and Std Dev)

	FE Q1	**FE Q2**	**FE Q3**	**FE Q4**	**FE Q5**
Annual VMT	10,900 8,660	10,200 8,860	9,910 8,030	9,650 8,090	9,620 8,060
Odometer	85,800 47,600	84,100 46,600	78,000 43,800	77,000 43,700	77,900 44,500
Avg Gas Price	2.33 0.56	2.3 0.565	2.31 0.563	2.3 0.565	2.3 0.564
Fuel Efficiency (MPG)	16.4 1.25	20.2 1.02	23.2 0.728	25.3 0.875	30.3 2.61
Unemployment (adj)	5.48 1.08	5.46 1.04	5.46 1.05	5.46 1.04	5.46 1.04
GDP	14,100 680	14,100 696	14,100 691	14,100 696	14,100 696