UNIVERSITY OF CALIFORNIA, SAN DIEGO

Three Essays in Energy Economics

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by

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ABSTRACT OF THE DISSERTATION

Three Essays in Energy Economics

by

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Professor Mark Jacobsen, Chair

This dissertation studies our relationship with energy, as individuals and as a society. In the first chapter, I look at individual response to gasoline prices by investigating the relationship between gasoline prices and running out of gasoline. In the second chapter I investigate household level short-run responses to gasoline prices by decomposing the traditional fuel use elasticity into changes in driving and change in average fuel economy. The third chapter looks at policies that comes as responses to environmental externalities associated with fuel use.

Chapter 1

Out of Gas

1.1 Introduction

Between the first quarter of 2010 to the first quarter of 2011, the Automobile Club of Southern California (AAA) reported a 12.9% increase in the number of service calls for cars that had run out of gas.[1] In other locations around the country, the increase in calls for gas-outs were even higher: 39% in Washington, D.C., 36.% in Maryland, and 36.8% in Virginia.[2] The price of gas is most often blamed for this increase. During this year, gas prices for a gallon of regular unleaded gas rose from $3.11 to $4.18 in California and $2.83 to $3.78 in the Mid-Atlantic region of the United States. News articles covering increases in gas-outs suggest that as a response to high prices, drivers are "pushing it, trying to buy few gallons and trying to make it home on less gas," or drivers "squeeze the most they can out of a gallon of gas."[3]

Although the price of gas is cited as the main culprit, no one has estimated the relationship between gas prices and gas-outs. Estimating this relationship is difficult because we are unable to observe the total number of gas-outs. Reports from auto clubs may not be representative because the members are a self selected group. The behavior of these drivers is interesting in its own right. "Pushing it" and getting every mile out of a gallon of gas is something that could be done even on a full tank. An explanation of trying to get the most out of the gas by driving in a way to achieve the highest fuel economy should not exclude a driver from also putting gas in the tank. Another explanation for running out of gas could be mean reversion. Drivers may hope that the gas price will be cheaper tomorrow and decide to wait. However, in my six years of data, the gas price never drops more than 2% in a given day and on average changes by less than $0.01 a day on average. If drivers are in fact waiting for lower prices, they take on risks of incurring substantial costs associated with running out of gas to save just pennies at the pump.

In this paper I estimate the relationship between gas prices and running out

[1] http://news.aaa-calif.com/news/auto-club-high-prices-may-mean-201558

[2] https://apps.midatlantic.aaa.com/siteapps/files/apps/safety/cms_release_content.asp?id=6663

[3] http://www.nytimes.com/2008/06/15/us/15stranded.html?ref=automobiles\&_r=0

of gas in California. I use data from the California Freeway Service Patrol, a fleet of tow trucks that patrols the highway and assists stranded drivers. The roving nature of these tow trucks provides a plausible random sample of the types of incidents on the freeway. I find a price elasticity of gas-outs of 0.7 along with evidence that monthly and weekly pay cycles may be a factor in gas-outs regardless of the gas price.

I calibrate this to a simple model of a cost minimizing driver and find that this elasticity would require drivers to have a combination of low discount factors and unrealistic beliefs about tomorrows gas price, or an extremely small cost of running out of gas. One reason for delaying gas purchases could be the fact that is unpleasant and the belief that it it will be less inconvenient tomorrow. I consider the effect this type of present bias on the driver and find that a small behavioral cost associated with filling up can support much more realistic estimates for the discount factor, beliefs about tomorrows gas price, and the cost of a gas-out relative to the cost of filling up. I estimate that this present bias leads to 6 times more gas-outs than if the present bias did not exist.

While this is among the first papers to estimate the relationship between gas prices and gas-outs, it adds to the growing literature on how consumers respond to gas price changes.[4] Studies have shown how price affects gasoline demand (Levin et al. (2015); Dahl and Sterner (1991); Espey (1998)), miles traveled (Gillingham (2013)), search behavior (Lewis and Marvel (2011)), driving speed (Burger and Kaffine (2009)), and vehicle choice (Gillingham (2010)). Since running out of gasoline implies that the miles traveled extended further than gasoline inventories, this paper suggests that the relationship between miles traveled and gasoline demand may not always tell us the same thing in the short run.

This paper also provides possible real-world evidence for time inconsistent preferences. Models of present bias and procrastination have been studied exten-

[4] Miller (2011) is the only other paper to my knowledge that studies gas outs. Some main differences in our approaches is Miller's use of monthly data, a different geographic location, and a focus on credit constraints as a driving factor. Our papers may possibly be differentiated in terms of a short-run versus medium-run elasticity of gas-outs as well as capturing trends in different regions

sively in theoretical and laboratory settings[5], but less has been done using real world data. This paper joins works such as Shapiro (2005) and DellaVigna and Malmendier (2006) that find time inconsistent behavior in food consumption and going to the gym. The model I adopt is in similar spirit to O'Donoghue and Rabin (1999) where I consider the behavior of time consistent drivers, sophisticated drivers, and naive drivers.

The rest of the paper is organized as follows. Section 1.2 describes the data used in estimation. Section 1.3 describes the estimation strategy. Section 1.4 presents the empirical results on how freeway incidents respond to gas prices. Section 1.5 builds a two period model of filling up gas for a time consistent individual and calibrates it to the data. Section 1.6 extends this model by adding in a behavioral component and compares outcomes between the different types of drivers. Finally, section 1.7 concludes.

1.2 Data

I combine three datasets for my analysis. To measure trends in freeway incidents, I use individual incident reports from the Freeway Service Patrol (FSP) in four different California districts. The FSP is a joint program provided by Caltrans, the California Highway Patrol, and local transportation agencies. The FSP program is a free service of privately owned tow trucks that patrol designated routes on congested urban California Freeways. While the FSP cannot assist all freeway incidents that occur, the roving nature of the trucks allow them to capture a sample of the types of incidents on the road. It typically operates Monday through Friday during peak commute hours. The goal of the FSP is to maximize the effectiveness of the freeway transportation system by removing freeway obstructions and assisting stranded drivers. The FSP is able to tow vehicles to the side of the road, offer a gallon of gasoline to drivers who have run out, help with other car problems, and change a flat tire. The four districts I have data for are: District 3 (Sacramento,

[5]See Frederick et al. (2002) for a survey of the literature.

Yolo, and Placer Counties), District 6 (Fresno County), District 8 (San Bernadino County), and District 11 (San Diego County).

The individual incident reports contain information on the date and time of the incident, the type of incident, and type of vehicle involved. For my analysis, I categorize incident types into gas-outs, flat tires, car problems, and all other FSP assists. Car problems includes overheating, electrical problems, and mechanical problems. All other FSP incidents includes accident assists, vehicle fires, lock outs, abandoned vehicles, debris removal, and anything categorized as "other". I categorize the types of vehicles into five groups: autos, small trucks, large trucks, motorcycles, and those listed as other or unknown.

The data for the price of gasoline comes from the Oil Price Information Service. I have California's daily average for gas price between July 1, 2006 to August 31, 2012. While there is some degree of heterogeneity of gas prices throughout California in the levels of gas price, the patterns in gas prices are generally the same among all districts. Finally, I use California's Performance Measurement System (PeMS) for estimates of daily vehicle miles traveled (VMT) for each of the four districts.[6]

I restrict my data to time periods where number of tow truck routes and tow trucks for a district remained constant and for which I have gas price data. I also restrict the data to weekdays. For each day, district, and vehicle type I observe the number of out of gas incidents, flat tires, car problems, and other FSP assists. Table 1.1 shows some summary statistics. We can see that there are possibly some inconsistencies for how the vehicle types are defined between districts or the make up

[6] There are data issues with PeMS-based estimates because of frequent changes in the configuration of the detector system. This has been pointed out by Kwon et al. (2006) and it has been recommended that care be taken when using PeMS data to make inter-year and inter-district comparisons. When looking at the VMT data, I find that high number a sensors is indicative of high recorded VMT. Also VMT is more volatile when there are more sensors. I adjust my measure of VMT by controlling for the number of sensors. Specifically, for each district I use residuals from a regression of log(VMT) on log(number of sensors) and year indicators to capture variation in VMT. These estimates are scaled so that the changes in the estimated VMT within a week is proportional to the change in the recorded VMT within a week. The main results remain unchanged even when using the recorded estimates of VMT.

of vehicles differs by district. In the estimation I will control for this by including district level interactions with vehicle type. In total I have 24,022 of these day, district, vehicle type observations.

1.3 Estimating patterns in freeway incidents

Define n_{it} as the number of freeway incidents of type i, during day t. Define $N_t = \sum_i n_{it}$ as the total number of freeway incidents on day t. The proportion of incidents of type i is $n_{it}/N_t = \omega_{it}$.

The challenge to estimating ω is n_{it} and N_t cannot be observed. To my knowledge, only the data on fatal accidents in the US comes close to observing all incidents of a specific type. Instead, I observe incidents covered by the California Freeway Service Patrol. Define m_{it} as the number of FSP assists of type i during day t and $M_t = \sum_i m_{it}$. I assume $m_{it} = \nu n_{it}$ for all incident types. For example, if the FSP assists 5% of all flat tires, it also assists 5% of all gas-outs. This is a reasonable assumption if the roving nature of the FSP trucks allows them to assist a random sample of the true number of freeway incidents that occur. Under this assumption, the true rate of each incident type can be observed:

$$\frac{m_{it}}{M_t} = \frac{\nu n_{it}}{\nu N_t} = \omega_{it} \tag{1.1}$$

I estimate this relationship in a count data framework, treating the number of FSP assists of type i as the dependent variable and setting the total number of FSP assists as the exposure.[7] I further subdivide incidents across FSP district, d, and

[7] Instead of the count data framework I also run the estimation as a fractional logit, estimating the ratio:

$$\frac{m_{ijdt}}{M_{dt}} = \omega_{ijdt}$$

The results are similar. For gas-outs, the fractional logit implies a price elasticity of the gas-out rate of 0.67.

vehicle type, j. This gives the following estimating equation:[8]

$$m_{ijdt} = M_{dt}\omega_{ijdt} \tag{1.2}$$

ω_{ijdt} is a function of economic, environmental, and engineering factors. I decompose ω into several multiplicative components, one of which is the gas price. Other factors affecting this rate will be vehicle miles traveled and various fixed effects for time, location, and vehicle type. I run the Poisson regression:

$$\begin{aligned} m_{ijdt} =& M_{dt} exp(\beta_0 + \beta_1 \log(p_t) + \beta_2 \log(VMT_t) \\ & + \beta_3 Year_t + \beta_4 Month_t + \beta_5 DOW_t + \beta_6 District_d \\ & + \beta_7 Type_j \times District_d) exp(\epsilon_{ijt}) \end{aligned} \tag{1.3}$$

where p_t is the daily gas price, VMT_t is vehicle miles traveled, $Year_t$, $Month_t$, and DOW_t are indicator variables for the year, month, and day of week. $Type_j$ is a vector of indicator variables for whether the vehicle involved is an auto, small truck, large truck, or motorcycle.

The main coefficient of interest is β_1 which gives the price elasticity of FSP assists of incident i. Under the assumption that the FSP incidents represent a fixed proportion of the total number of incidents, this price elasticity is also the price elasticity of n_{it}. If instead we believe there are capacity constraints on the number of FSP assists that are possible such that we see a smaller increase in FSP incidents compared to the true increase, then the price elasticity we estimate is a lower bound for the true price elasticity.

There may be concern that if drivers know have knowledge about the FSP, they may intentionally change their behavior. For District 11, I also have data from surveys given to drivers who had been assisted. Of drivers who responded, 73%

[8] I also consider the estimation strategy where $m_{ijdt} = M_{djt}\omega_{ijdt}$. Here, M_{djt} is the total number of FSP incidents in district d, for vehicle type j, on day t. This version of the estimation drops about 3,000 observations where there are no FSP assists for a specific vehicle type but there is still variation in FSP assists for other types of vehicles as well as variation in prices and VMT. I have run both specifications and the results are nearly identical.

had never heard of the FSP before. Furthermore, FSP operators will ask drivers to try to start their vehicles before giving a gallon of gasoline. This suggests strategic gas-outs are probably not driving the results.

β_2 - β_5 capture a variety of economic and environmental conditions that influence the count of freeway incidents. This includes factors related to freeway congestion, pay cycle effects, and driving patterns that vary systematically throughout the week. β_6 controls for heterogeneity among districts. This could capture things like weather and demographics. β_7 captures the engineering factor associated with freeway incidents by separating effects out for cars of different sizes. Vehicle type is interacted with district indicator variables due to differences between districts in classifying variable types and the composition of vehicles in districts. This coefficient may give insight into differences among different types of car users.

1.4 Empirical Results

I focus my attention on three specific types of FSP incidents. I believe gas-outs reveal a behavioral response to the price of gas. On the other hand, flat tires and car problems will not respond in the same way to changes in the gas price.

1.4.1 Graphical analysis

I begin with simple graphical representations of the data. Figure 1.1 contrasts smoothed trends of out of gas counts, flat tires, and car problems with gas prices. The figure shows that spikes in the gas price are generally associated with jumps in gas-outs. Flat tires on the other hand look like they have a strong seasonal pattern but otherwise move independently of the gas price. Car problems also appear to exhibit strong seasonal characteristics. It is unclear just from the graphic whether it moves with price.

One explanation of why people run out of gas when the price is high is because of credit constraints or pay cycle effects. If we assume that many people are paid on the last day or first day of the month, we may expect to see larger counts of gas-outs near the end of the month. We might also expect to see the same pattern during the week for people paid weekly. Figure 1.2 plots the daily deviations from the monthly average gas-outs and compares this with flat tires and car problems. The figure shows that during the beginning of the month, gas-outs are generally lower than the monthly average. Gas-outs then increase to being above average by the second and third week of the month. During the fourth week of the month out of gas counts are sometimes below average. The days near the end of the month have the the most gas-outs on average. On the other hand, both flat tires and car problems are highest in the beginning of the month and appear to be the lowest at the end of the month.

Figure 1.3 plots the deviations from the weekly average for out of gas counts, flat tires, and car problems. It shows a clear increasing trend for out of gas counts throughout the week. Flat tires do not appear to exhibit any within week trends. Car problems are highest on Friday are otherwise constant during the rest of the week.

1.4.2 Estimation results

I now quantify the findings more precisely

Table 1.2 shows the estimation of specification (1.3). The first 4 columns have no restrictions on parameter coefficients while the last four columns restrict the number daily FSP assists in each district, M, as the exposure. The results for the price elasticity of each incident remains similar in both the restricted and unrestricted models.

The main result of table 1.2 appears in columns 1 and 4. It tells us that a 1% increase in the price of gasoline results in a 0.7% increase in gas-outs. The other columns show negative statistically significant price effect on car problems, flat tires, and all other FSP assists. These estiamtes on tires and car problems appear to speak against my hypothesis that gas prices should have no effect in these incidents. However, these estimates can be attributed to a mechanical relationship. If we hold the total number of FSP assists constant and increase the number of out of gas counts then there must be an equal decrease in all other FSP assists. To illustrate this explicitly, out of gas incidents, car problems, flat tires, and other FSP assists make up 11.15%, 23.95%, 16.53%, and 48.35% of the incidents we observe. Multiplying each of these proportions by the price coefficient and adding the together shows a total change in FSP incidents equal to 0.[9]

The coefficients on log(M) in the first four columns show how each of the various incident types actually increase in response to an increase in the total number of FSP assists. This would be the appropriate specification if we thought the daily number of incidents affected incident counts in ways other than increasing the opportunity for more observed incidents. If we increase the total number of FSP assists by 1%, out of gas counts, car problems, and flat tires increase by less than 1%. The remainder of the increase is found in other FSP incidents.[10]

The log(VMT) coefficients can tell us that when VMT is high, the number of total incidents increases. A 1% increase in VMT leads to a 1.23% increase in FSP assists.[11] The positive and significant coefficients on problems would be consistent with more cars overheating due to congested freeways. The positive and significant coefficient on flat tires would be consistent with heavily used freeways having more debris and obstructions that could damage tires.

District heterogeneity

Table 1.3 shows a positive and significant price elasticity of out of gas counts holds far all districts individually and some degree of heterogeneity among the districts. In the restricted model, the coefficient on log(price) for District 3 is 63% higher than in District 11. Demographic characteristics may be able to explain some of this variation. District 11 has an annual median household income that is almost \$7,000 higher than that of District 3. However the inverse relationship between wealth and gas-outs does not hold for all districts. District 8 has the second highest median income and also has the second highest price elasticity. The coeffi-

[9] $(11.15 \times 0.706) + (23.95 \times -0.115) + (16.53 \times -0.170) + (48.53 \times -0.0522) = 0$

[10] $(11.15 \times 0.791) + (23.95 \times 0.870) + (16.53 \times 0.855) + (48.53 \times 1.148) = 1$

[11] $(11.15 \times -0.0282) + (23.95 \times 0.291) + (16.53 \times 0.266) + (48.53 \times -0.203) = 1.236$

cients on log(M) in the first four columns shows that in District 6 and 11, gas-outs move almost proportionally to the total number of FSP assists. In district 3, gas outs do not increase proportionally to the total number of FSP assists. Finally, the coefficients on VMT tell the same story as in the aggregate regression.

Tables 1.4, 1.5, and 1.6 show district heterogeneity for for car problems, flat tires, and all other FSP assists.

Pay cycles and credit constraints

Table 1.7 presents results that point towards pay cycle or credit constraints as a contributing factor to gas-outs. I add in week of month indicators to equation (1.3) and report the coefficients on the day of week and week of month coefficients. The first week of the month and the first day of the week are omitted so that all the coefficients represent a change relative to these times. Column 1 indicates that the first week of the month has the fewest gas-outs. By the end of the month, we should expect 7% more out gas-outs than at the beginning of the month. The increasing trend by the day of the week is also clear from the regressions with a 12-13% increase in out of gas incidents on Thursday and Friday than compared to Mondays. Wald tests also reject the increase on Friday being the same as the increase on either Tuesday or Wednesday.

Columns 2 and 3 present how flat tires and car problems change throughout the month. Both of these types of incidents do not appear to have any discernible pattern during the month. On several of the day of the week, the coefficients are negative and significant for flat tires and car problems. As before, these can be explained as counteracting the positive coefficient on out of gas counts since the number of total FSP assists is being held constant.

The week of month and day of week effects reported here occur regardless of the gas price. We can also look at the effect of gas prices at certain times during the month and week. Table 1.8 shows the results of two regressions. The top shows the results of interacting the day of the week with log(price). There appears to be a decreasing trend in the price effect as the week progresses; a change in price of 1%

on Monday predicts an increase in gas-outs of 0.823% while on Friday the increase in out of gas counts would be 0.520%. This is also consistent with a story of credit constraints. If people are wealthier on Mondays, they are able to purchase gas more readily. When gas prices are high on a Monday, these drivers may wait for prices to go down during the week resulting in more Monday gas-outs. On the other hand, high prices will not have as big of an influence on Friday if indiviuals are already credit constrained and would have run out of gas regardless of the price.

The bottom panel of table 1.8 shows the results from interacting week of month with price. There doesn't appear a trend for the price elasticity during specific weeks of the month. The price elasticity is strongest in weeks 3 and 4 and lowest on week 5.

Vehicle heterogeneity

It is possible to look at price interactions with vehicle type to gain insight into exactly who is most affected by the gas price. Table 1.9 provides these estimates, showing the price elasticities for each vehicle type. Column 1 indicates that of cars that we can classify, small trucks and SUVs respond the most to changes in the gas price while large trucks respond the least. One explanation for this is large trucks are often not personal vehicles but instead used for business. If the drivers of these vehicles are not paying for gasoline out of their own pockets then we wouldn't prices to have a large effect. Surprisingly, motorcycles have the largest price elasticity although they generally have the highest fuel economy. One explanation for this could be the small gas tank capacity.

The results show that the price elasticity of running out of gas is close to 0.7. Pay cycle effects and credit constraints may play a role, but controlling for observed environmental and economic conditions does not make the price effect go away. In the next section I develop a simple 2 period decision problem and fit its parameters to what the data has revealed to us.

1.5 2-period decision problem of whether to fill up

Consider a cost minimizing driver who is deciding whether to get gas today or get gas tomorrow. He expects prices tomorrow may be different than today so that if today's cost to fill up gas are α, tomorrows cost will be $\gamma\alpha$. This formulation assumes that the amount of gasoline purchased today versus tomorrow remains the same but does not put restrictions on the actual quantity. Let ϕ be the probability the driver runs out of gas today given his current inventory of gas. If the driver runs out of gas he incurs a cost of c and ends up getting gas at todays price α. If he decides to get gas today he will not run out of gasoline.

This driver will fill up today if he expects the costs today are cheaper than filling up tomorrow and incurring a risk of running out of gas:

$$\alpha < \phi(c+\alpha) + (1-\phi)\delta\gamma\alpha \tag{1.4}$$

where δ is the daily discount rate.

I re-write the relationship so I can look at how various factors affect the gas-out risk the driver will take on. The driver will get gas today if:

$$\phi > \frac{(1-\delta\gamma)\alpha}{c+(1-\delta\gamma)\alpha} \tag{1.5}$$

1.5.1 Defining $\hat{\phi}$

Define:

$$\hat{\phi} = \frac{(1-\delta\gamma)\alpha}{c+(1-\delta\gamma)\alpha} \tag{1.6}$$

This is the threshold gas-out risk. When $\phi > \hat{\phi}$, the driver will decide to get gas. Figure 1.4 plots out $\hat{\phi}$ and how it responds to the price of gas and costs of gas-outs for $\delta\gamma = .97$. It shows that when the cost of filling up is very cheap, drivers should fill up more often. As gas prices increases, drivers take on more gas-out risk due to discounting and the possibility that gas prices may go down. In this model, a driver who values expenditures today the same as expenditures tomorrow will always get gas today if he believes the price of gas tomorrow will be the same or higher than today. The figure also shows how drivers take on more gas-out risk when the costs of running out of gas are low.

We can look explicitly at how increases in the price of gas affects $\hat{\phi}$.

$$\frac{d\hat{\phi}}{d\alpha} = \frac{(1-\delta\gamma)c}{[c+(1-\delta\gamma)\alpha]^2} \tag{1.7}$$

As an elasticity we have:

$$E_{\hat{\phi},\alpha} = \frac{c}{c+(1-\delta\gamma)\alpha} \tag{1.8}$$

1.5.2 Can $\hat{\phi}$ tell us about the number gas-outs?

Vehicles with $0 < \phi < \hat{\phi}$ do not fill up and are at risk of running out of gas. This tell us that the number of gas-outs comes from these vehicles multiplied by the expected value of ϕ conditional on not filling up. Let $f(\phi)$ be the distribution of ϕ among vehicles. Then the number of gas-outs is:

$$\begin{aligned} n_{gas} &= \frac{\int_0^{\hat{\phi}} \phi f(\phi)d\phi}{\int_0^{\hat{\phi}} f(\phi)d\phi} \int_0^{\hat{\phi}} f(\phi)d\phi \times C && (1.9) \\ &= \int_0^{\hat{\phi}} \phi f(\phi)d\phi \times C && (1.10) \end{aligned}$$

where C is the number of vehicles that are driven.

Assume C remains constant for changes in the gas price. Our assumption in the estimation section that $m_{gas} = \nu n_{gas}$ implies that the price elasticity of FSP gas-outs equals the true price elasticity of gas-outs. This gives us:

$$E_{m_{gas},p} = 0.7 = E_{\int_0^{\hat{\phi}} \phi f(\phi)d\phi,p} \tag{1.11}$$

We then need to establish whether there exists reasonable parameter values that will fit this relationship. Towards this goal, I consider three different distributions for $f(\phi)$, each implying a different structure on how the gas-out risk is distributed among vehicles.

1. The Uniform Distribution

$$f(\phi) = \begin{cases} x, & \text{if } 0 \le \phi \le 1 \\ 0, & \text{o.w.} \end{cases}$$

   where $x \le 1$. If $x < 1$, I assume a mass of vehicles with $\phi = 0$. Allowing $x < 1$ means the probability of running out of gas is not a linear function of how much gas is in the tank. For example, the probability of running out of gas when the tank is full is probably 0 for most drivers and is probably the same if the tank is 3/4 full. There is some threshold of gas in the tank that must be passed for there to be any positive probability of running out of gas. The uniform distribution implies gas-out risk is randomly distributed among these cars.

   Under the uniform distribution, we then have:

$$n_{gas} = \hat{\phi}^2 \times C, \tag{1.12}$$

   and equation (1.11) becomes:

$$2E_{\hat{\phi},\alpha} = 0.7 \tag{1.13}$$

2. Skewed Right Distribution

$$f(\phi) = \begin{cases} y - y\phi & \text{if } 0 \le \phi \le 1 \\ 0, & \text{o.w.} \end{cases}$$

   where $y \le 2$. If $y < 2$, the remaining mass of drivers are given a value of

$\phi = 0$. This distribution implies that most people do not face a high risk of running out of gas. With this specification,

$$m_{gas} = \left(\frac{y}{2}\hat{\phi}^2 - \frac{y}{3}\hat{\phi}^3\right) \times C \tag{1.14}$$

and equation (1.11) becomes:

$$6\left(\frac{1-\hat{\phi}}{3-2\hat{\phi}}\right) E_{\hat{\phi},\alpha} = 0.7 \tag{1.15}$$

3. Skewed Left Distribution

$$f(\phi) = \begin{cases} z\phi & \text{if } 0 \le \phi \le 1 \\ 0, & \text{o.w.} \end{cases}$$

where $z \le 2$. If $z < 2$ then the remaining mass of drivers are given a value of $\phi = 0$. This distribution implies that for vehicles with a positive probability of running out of gas, the majority of these vehicles have a high risk. With this specification,

$$m_{gas} = \frac{z}{3}\hat{\phi}^3 \times C \tag{1.16}$$

an equation (1.11) becomes:

$$3E_{\hat{\phi},\alpha} = 0.7 \tag{1.17}$$

Figure 1.5 plots $E_{\int_0^{\hat{\phi}} \phi f(\phi) d\phi, p}$, the price elasticity of gas-outs in the model, against $\delta\gamma$ for a variety of gas-out costs and for the three different distributions. The horizontal line at 0.7, indicates the price elasticity of gas-outs from the data. The point at which the horizontal line intersects another curve pins down values $\delta\gamma$ and ratio c/α needed to fit the the model to the data. For example, if the cost of a gas-out is the same as the cost of a fill-up and ϕ is distributed uniformly, the combined effects of discounting and beliefs about tomorrows gas price would require $\delta\gamma \approx 0.35$ for behavior in the model to match what is seen in the data. The figure shows that for a variety of c/α ratios, $\delta\gamma$ would need to be much less than 1.

It is unlikely that the true value of $\delta\gamma$ is much less than 1. A large body of work in estimating time preferences find annual discount factors in the range of 0.6 to 1.[12] This would imply a daily discount factor would need to be very close to 1. Furthermore, gas prices do not change much day to day. The largest decrease in the gas price in a single day is 2%. Thus, even if drivers were being very optimistic about tomorrows gas price, we would not expect a value of $\delta\gamma$ less than about 0.97. At this level of $\delta\gamma$, even a c/α ratio of 0.05 is not low enough so that the model can fit the data. If $\delta\gamma$ were close to 1, the ratio of c/α would have to be very close to 0.

I also believe it is unlikely that the costs of a gas-out so low that c/α approaches 0. Besides the time costs associated with running out of gas there are dangers associated with power steering and brakes not working properly when the car engine turns off. For some vehicles, running out of fuel may result in damage to the fuel pump. The cost to replace a fuel pump can be $500 dollars or more in parts and labor.[13] For drivers not aware of the FSP program, there are also possible costs that would need to be paid for towing a disabled vehicle.

Thus, I find that when calibrated to the data, this simple two period model gives unrealistic relationships among the parameters. It suggests that drivers would need to have low discount factors, unreasonable beliefs about tomorrows gas price, or low costs associated out of gas. In the next section I build in a behavioral component into the model to see if this helps provide more realistic parameter estimates.

1.6 A behavioral component?

Going to the gas station and filling up the tank is an unpleasant activity. Along with the time cost associated with stopping to get gas there may also be a

[12] See Frederick et al. (2002) for a survey

[13] http://newsroom.aaa.com/2011/04/aaa-reminds-motorists-of-hazards-of-running-out-of-gas/

psychic cost that must be overcome. Activities with immediate costs often result in procrastination. In this section I look at how adding a psychic cost to filling up gas changes the threshold gas-out risk.

A typical way to model this decision making process is using $\beta - \delta$ preferences. However, in a two period model the differences between standard exponential discounting and $\beta - \delta$ preferences would be difficult to identify. Instead I impose the psychic cost in an additive manner.

I model the decision to fill up for two types of individuals, similar to O'Donoghue and Rabin (1999). First I consider the behavior of "sophisticated" individuals. These are people who understand that the psychic costs of filling up today will also be faced tomorrow if getting gas is put off. Second, I look at "naive" individuals. These are people who take into account the psychic cost today but do not think they'll face the same inconvenience costs if they filled up tomorrow. To be consistent with the behavioral economics literature, I will refer to the first type of driver we considered as a time consistent driver.

1.6.1 Sophisticated decision makers

Re-write the decision problem so that a driver will fill up if:

$$b + \alpha < \phi(c + b + \alpha) + (1 - \phi)\delta(\gamma\alpha + b), \tag{1.18}$$

where b is the behavioral cost associated with filling up gas. The sophisticated driver incurs a behavioral cost of filling up but realizes he will also face this cost tomorrow if he waits or later today if he runs out of gas. One way we can think of b in this setting is a time cost that the driver factors into his everyday decisions. This decision problem implies a threshold out of gas risk of

$$\hat{\phi} = \frac{\alpha(1 - \delta\gamma) + b(1 - \delta)}{\alpha(1 - \delta\gamma) + b(1 - \delta) + c}, \tag{1.19}$$

and a price elasticity of threshold out of gas risk of

$$E_{\hat{\phi},\alpha} = \frac{\alpha c(1-\delta\gamma)}{[\alpha(1-\delta\gamma)+b(1-\delta)+c][\alpha(1-\delta\gamma)+b(1-\delta)]} \tag{1.20}$$

One difference between the sophisticated driver and the time consistent driver is the possibility of taking on small gas-out risks even when the price of gas is very low. This is because of the behavioral cost that must be paid whenever going to the pump. Discounting makes this behavioral cost smaller in future periods. A second difference is the possibility of waiting to fill up even if the cost of gas may increase tomorrow. Nonetheless, the gas-out risk and the price elasticity of gas-out risk for the sophisticated driver is still quite similar to the time consistent driver.

Figure 1.6 fixes $\delta = 0.99$, $\gamma = 0.98$ and shows how $\hat{\phi}$ changes with the ratio of gas-out cost to gas price for varying behavioral costs. We can see that changes in the size of the behavioral cost has a very small impact on the optimal gas-out risk. Figure 1.7 maintains these same values for δ and γ and plots the price elasticity of the conditional expectation of gas-out risk on the ratio c/α for the three different distributions. The intersection of the horizontal line and a curve pin down parameter values such that the model would be consistent with the data. The figure shows that regardless of the distribution or behavioral cost, the sophisticated driver still needs an unreasonably small c/α ratio if the discount factor is large and beliefs about the gas price tomorrow are realistic. In terms of the relationships between parameters, the sophisticated driver looks almost identical to the time consistent driver.

1.6.2 Naive decision makers

Re-write the problem so that the driver decides to fill up if:

$$b + \alpha < \phi(c+\alpha) + (1-\phi)(\delta\gamma\alpha) \tag{1.21}$$

This driver takes into account the behavioral cost of filing up gas today but does not believe he will encounter these costs if he decides to fill up tomorrow.

We can solve for the threshold gas risk:

$$\hat{\phi} = \frac{b + \alpha(1 - \delta\gamma)}{c + \alpha(1 - \delta\gamma)} \tag{1.22}$$

and the elasticity of threshold gas risk:

$$E_{\hat{\phi},\alpha} = \frac{(c - b)\alpha(1 - \delta\gamma)}{(b + \alpha(1 - \delta\gamma))(c + \alpha(1 - \delta\gamma))} \tag{1.23}$$

Unlike the sophisticated and time consistent drivers, the naive driver will take on some risk of running out of gas even if there is no discounting and if the costs of gas tomorrow will be the same as today. Furthermore, this risk is much larger than the sophisticated driver's risk for values of $\delta < 1$. Like the sophisticated individual, the naive driver may also wait to get gas even if he believes the price of gas will be higher tomorrow.

The higher threshold gas-out risk for naive drivers may help fit the model to the data when considering the price elasticity of gas-outs. We saw for the time consistent and sophisticated drivers, that the price elasticity of gas-outs in the model was higher than the data's price elasticity. For small values of the behavior cost, the value of $d\hat{\phi}/d\alpha$ is similar for all three types of drivers. Since the threshold gas-out risk is at a higher level for the naive driver, the proportional change in gas-outs will be smaller.

Figure 1.8 shows he path of $\hat{\phi}$ for varying behavioral costs. Unlike before, we can now see that the behavioral cost shifts the threshold gas-out risk. Higher behavioral costs are associated with taking more risks with running out of gas. Figure 1.9 plots the elasticity of gas-outs due to the gas-out risk for Naive drivers. Unlike the similar figure for the sophisticated driver, these graphs suggest more realistic c/α ratios. For example, if ϕ has a uniform distribution, it appears like a behavioral cost close to 5% of the fill-up cost would make behavior in the model fit the data for a wide range of c/α. If a fill-up costs \$40 dollars and there is a \$2 pyschic cost that must be overcome to stop at the gas station then we should expect to see a 0.7% rise in out of gas counts if gas prices went up by 1%.

For the left skewed distribution a higher behavioral cost or a little less than 10% of the fill-up cost would be needed. For the right skewed distribution, a behavioral cost of perhas 2.5% of the fill-up cost would be needed.

1.6.3 Welfare

Small values of the behavioral cost can have large implications for how individuals respond to changes in the gas price. In this section I look at how these behavioral costs influence the total number of gas-outs. Figure 1.10 plots the gas-out risk against the ratio of c/α for the time consistent drivers, sophisticated drivers, and naive drivers. The figure is calibrated to a discount factor of 0.99, beliefs that the gas price will be 2% cheaper tomorrow, and a behavioral cost of running out of gas that is 5% of the fill-up cost as suggested from the uniform distribution. In the figure it appears as if the sophisticated and time consistent driver take the same gas-out risk. In reality, both the sophisticated and naive drivers take on higher gas-out risk for every level of c/α but naive drivers take on much more risk than sophisticated drivers.

We can get the proportional increase in out of gas counts by looking at the difference between the gas-out risks. The increase will be $\hat{\phi_S}^2 - \hat{\phi_{TC}}^2$ for increases from sophisticated drivers and $\hat{\phi_N}^2 - \hat{\phi_{TC}}^2$ as the increases from Naive drivers. Figure 1.10 plots these values for the varying levels of c/α. If drivers were all naive, there would be more than 6.17 times as many gas-outs than if drivers were all time consistent and slightly less than 6 times as many gas-outs than if drivers were all sophisticated. Sophisticated drivers would result in 0.03 times as many gas-outs compared to a world with only time consistent drivers. We can also compare the differences in gas-outs between naive and sophisticated drivers when the price of gas is thought to be increasing. In this case, naive drivers result in about 5.93 times more gas-outs than sophisticated drivers.

Along with the costs that are incurred by the driver, gas-outs also have an external cost on society by contributing to freeway congestion. Recker et al. (2005) look at the effect of traffic incidents on delay and finds the median delay from a traffic incident is 86 vehicle hours. A typical way to deal with negative externalities is to propose a tax, perhaps fining drivers who run out of gas.[14] In response to a tax, the threshold gas-out risk would decrease. However, naive drivers would still contribute to about 6 times more gas-outs. Perhaps a more efficient policy measure would be making drivers aware of their time inconsistent behaviors.

1.7 Conclusion

This paper is the first to estimate the relationship between gas prices and gas-outs and challenges the notion of time consistent and even sophisticated behavior among drivers. In contrast, time inconsistent beliefs may be more consistent with my findings. These results may inform any other situations where people carry inventories of goods. Understanding more about consumer behavior in this respect is important especially if this behavior imposes negative externalities on others.

Chapter 1, in part, is currently being prepared for submission for publication of the material. Leung, William. The dissertation author was the primary investigator and author of this material.

[14]This is in fact what happens with the SAFEClear program in Houston, TX. While this used to be a free service similar to the FSP, due to budgetary constraints stranded vehicles are now charged \$50 for a tow and \$30 for On-freeway roadside services.

Table 1.1: Summary Statistics

district	Date Range	Veh. Type	Out of gas	Flat tire	Car Problems	Other	Total
		Auto	13,021	20,945	29,229	62,950	126,145
	7/3/2006	Small Truck	8,259	8,974	12,370	30,758	60,361
3	-	Large Truck	613	1,047	2,491	4,670	8,821
	6/29/2012	Motorcycle	423	139	583	1,029	2,174
		Other	261	738	1,017	9,308	11,324
		Auto	1,809	1,703	4,563	4,491	12,566
	7/3/2006	Small Truck	386	222	653	404	1,665
6	-	Large Truck	11	15	156	55	237
	7/27/2012	Motorcycle	10	0	6	5	21
		Other	86	54	150	730	1,020
		Auto	8,045	18,140	22,214	32,469	80,868
	7/3/2006	Small Truck	9,157	13,710	14,844	33,015	70,726
8	-	Large Truck	748	2,056	6,132	36,060	44,996
	6/29/2012	Motorcycle	288	113	317	743	1,461
		Other	77	151	411	12,930	13,569
		Auto	16,992	24,839	37,447	42,389	121,667
	7/3/2006	Small Truck	6,057	6,183	9,746	13,220	35,206
11	-	Large Truck	295	463	1,498	1,849	4,105
	6/30/2010	Motorcycle	556	119	493	734	1,902
		Other	836	1,146	1,601	6,808	10,391

Table 1.2: Price effects on FSP incidents

	Unrestricted				Restricted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Out of gas	Problems	Flat tire	Other	Out of gas	Problems	Flat tire	Other
log(price)	0.706***	-0.115***	-0.170***	-0.0522***	0.682***	-0.130***	-0.185***	-0.0397**
	(0.0384)	(0.0256)	(0.0319)	(0.0189)	(0.0389)	(0.0257)	(0.0320)	(0.0192)
log(VMT)	-0.0282	0.291***	0.266**	-0.203***	-0.0283	0.297***	0.281**	-0.226***
	(0.139)	(0.0846)	(0.123)	(0.0696)	(0.137)	(0.0867)	(0.127)	(0.0715)
log(M)	0.791***	0.870***	0.855***	1.148***	1	1	1	1
	(0.0207)	(0.0151)	(0.0181)	(0.0126)	(0)	(0)	(0)	(0)
Observations	24,022	24,022	24,022	24,022	24,022	24,022	24,022	24,022

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions contain year, month, day of week, district, and vehicle type x district level fixed effects

Table 1.3: District heterogeneity in gas prices

	Unrestricted				Restricted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	District 3	District 6	District 8	District 11	District 3	District 6	District 8	District 11
VARIABLES	Out of gas	Out of gas	Out of gas	Out of gas	Out of gas	Out of gas	Out of gas	Out of gas
log(price)	0.787***	0.718***	0.797***	0.514***	0.850***	0.731***	0.767***	0.519***
	(0.0812)	(0.243)	(0.0765)	(0.0544)	(0.0809)	(0.242)	(0.0755)	(0.0536)
log(VMT)	0.268	0.242	0.0707	-0.0758	0.686**	0.228	0.113	-0.0656
	(0.268)	(0.451)	(0.289)	(0.262)	(0.268)	(0.452)	(0.286)	(0.262)
log(M)	0.561***	1.058***	0.820***	1.026***	1	1	1	1
	(0.0381)	(0.0537)	(0.0565)	(0.0439)	(0)	(0)	(0)	(0)
Observations	7,366	4,607	7,471	4,578	7,366	4,607	7,471	4,578

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions contain year, month, day of week, and vehicle type fixed effects.

Table 1.4: District heterogeneity in car problems

	Unrestricted				Restricted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	District 3	District 6	District 8	District 11	District 3	District 6	District 8	District 11
VARIABLES	Problems	Problems	Problems	Problems	Problems	Problems	Problems	Problems
log(price)	0.0909	-0.325***	-0.220***	-0.184***	0.135**	-0.368***	-0.235***	-0.175***
	(0.0566)	(0.112)	(0.0486)	(0.0379)	(0.0573)	(0.114)	(0.0483)	(0.0371)
log(VMT)	0.382*	0.368*	0.0446	0.185	0.646***	0.396*	0.0758	0.204
	(0.204)	(0.217)	(0.198)	(0.127)	(0.212)	(0.220)	(0.199)	(0.127)
log(M)	0.731***	0.851***	0.899***	1.046***	1	1	1	1
	(0.0314)	(0.0317)	(0.0406)	(0.0304)	(0)	(0)	(0)	(0)
Observations	7,366	4,607	7,471	4,578	7,366	4,607	7,471	4,578

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions contain year, month, day of week, and vehicle type fixed effects.

Table 1.5: District heterogeneity in flat tires

	Unrestricted				Restricted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	District 3	District 6	District 8	District 11	District 3	District 6	District 8	District 11
VARIABLES	Flat tire	Flat tire	Flat tire	Flat tire	Flat tire	Flat tire	Flat tire	Flat tire
log(price)	-0.0518	-0.324	-0.145***	-0.169***	0.00253	-0.314	-0.146***	-0.177***
	(0.0701)	(0.248)	(0.0524)	(0.0486)	(0.0708)	(0.246)	(0.0522)	(0.0481)
log(VMT)	0.792***	-0.00348	0.877***	0.183	1.147***	-0.0132	0.879***	0.166
	(0.253)	(0.466)	(0.252)	(0.186)	(0.262)	(0.465)	(0.252)	(0.187)
log(M)	0.657***	1.040***	0.992***	0.958***	1	1	1	1
	(0.0382)	(0.0562)	(0.0434)	(0.0333)	(0)	(0)	(0)	(0)
Observations	7,366	4,607	7,471	4,578	7,366	4,607	7,471	4,578

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions contain year, month, day of week, and vehicle type fixed effects.

Table 1.6: District heterogeneity in other FSP assists

	Unrestricted				Restricted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	District 3	District 6	District 8	District 11	District 3	District 6	District 8	District 11
VARIABLES	Other	Other	Other	Other	Other	Other	Other	Other
log(price)	-0.150***	0.226*	0.00482	0.0156	-0.206***	0.187	0.0151	0.00804
	(0.0340)	(0.121)	(0.0324)	(0.0345)	(0.0346)	(0.123)	(0.0320)	(0.0340)
log(VMT)	-0.411***	-0.246	-0.290**	-0.178	-0.720***	-0.209	-0.311**	-0.193
	(0.137)	(0.235)	(0.135)	(0.138)	(0.140)	(0.233)	(0.135)	(0.136)
log(M)	1.330***	0.854***	1.068***	0.963***	1	1	1	1
	(0.0278)	(0.0336)	(0.0255)	(0.0283)	(0)	(0)	(0)	(0)
Observations	7,366	4,607	7,471	4,578	7,366	4,607	7,471	4,578

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions contain year, month, day of week, and vehicle type fixed effects.

Table 1.7: Week of month and day of week averages

VARIABLES	(1) Out of gas	(2) Flat tire	(3) Problems	(4) Other
Week 2	0.0333***	-0.00617	-0.00289	-0.00408
	(0.0125)	(0.0106)	(0.00859)	(0.00668)
Week 3	0.0395***	-0.0111	-0.0101	-0.000677
	(0.0124)	(0.0104)	(0.00849)	(0.00657)
Week 4	0.0350***	-0.00899	-0.00290	-0.00327
	(0.0134)	(0.0109)	(0.00895)	(0.00695)
Week 5	0.0743***	-0.0146	-0.0178	-0.00236
	(0.0158)	(0.0135)	(0.0109)	(0.00831)
Tuesday	0.0328**	-0.0154	-0.0191**	0.00692
	(0.0142)	(0.0115)	(0.00948)	(0.00734)
Wednesday	0.0691***	-0.0296**	-0.0289***	0.00862
	(0.0143)	(0.0116)	(0.00968)	(0.00748)
Thursday	0.130***	-0.0634***	-0.0309***	0.00749
	(0.0150)	(0.0128)	(0.0102)	(0.00777)
Friday	0.121***	-0.0881***	-0.0255**	0.0150
	(0.0191)	(0.0167)	(0.0125)	(0.00988)
Observations	24,022	24,022	24,022	24,022

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Regressions only showing coefficients on week of month and day of week fixed effects. Wald tests reject out of gas counts in week 5 being equal weeks 2, 3, or 4 at .01, .02, and .01 significance levels. Wald tests reject out of gas counts on Thursday being equal to out of gas counts earlier in the week with p-value <.01. Wald test rejects out of gas counts on Friday being equal to out of gas counts on Tuesday or Wednesday with p-value <.01. Leaving the 1st of the month out of Week 1 gives the same results.

Table 1.8: Price interacted with day of week and week of month

VARIABLES	(1) Out of gas
Monday x log(price)	0.823***
	(0.0639)
Tuesday x log(price)	0.744***
	(0.0603)
Wednesday x log(price)	0.664***
	(0.0598)
Thursday x log(price)	0.668***
	(0.0606)
Friday x log(price)	0.520***
	(0.0597)
Week 1 x log(price)	0.672***
	(0.0588)
Week 2 x log(price)	0.642***
	(0.0581)
Week 3 x log(price)	0.709***
	(0.0544)
Week 4 x log(price)	0.724***
	(0.0632)
Week 5 x log(price)	0.619***
	(0.0810)
Observations	24,022

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

Notes: Table shows the results of 2 regressions. One with day of week and price interactions. The other with week of month and price interactions.

Table 1.9: Price interactions with vehicle type

VARIABLES	(1) Aggregate Out of gas	(2) District 3 Out of gas	(3) District 6 Out of gas	(4) District 8 Out of gas	(5) District 11 Out of gas
Autos and vans	0.616***	0.719***	0.456*	0.856***	0.530***
	(0.0422)	(0.0887)	(0.246)	(0.0907)	(0.0595)
Small trucks and SUVs	0.719***	1.011***	2.543***	0.728***	0.464***
	(0.0483)	(0.0981)	(0.447)	(0.0862)	(0.0783)
Large trucks	0.338**	0.440*	-2.768***	0.191	1.005***
	(0.143)	(0.245)	(0.987)	(0.222)	(0.275)
Motorcycles	0.996***	1.511***	-0.619	1.303***	0.580**
	(0.166)	(0.305)	(1.868)	(0.356)	(0.240)
Other	1.196***	3.295***	4.463***	0.655	0.482**
	(0.186)	(0.449)	(0.871)	(0.544)	(0.219)
Observations	24,022	7,366	4,607	7,471	4,578

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

Notes: All regressions are the constrained model, setting the coefficient on log(M) to 1. Results are similar for the unrestricted model. All regressions also include log(VMT). Column (1) regression contains district fixed effects along with district interactions with vehicle type, year, month, and day of week fixed effects. Columns (2)-(5) include year, month, and day of week fixed effects.

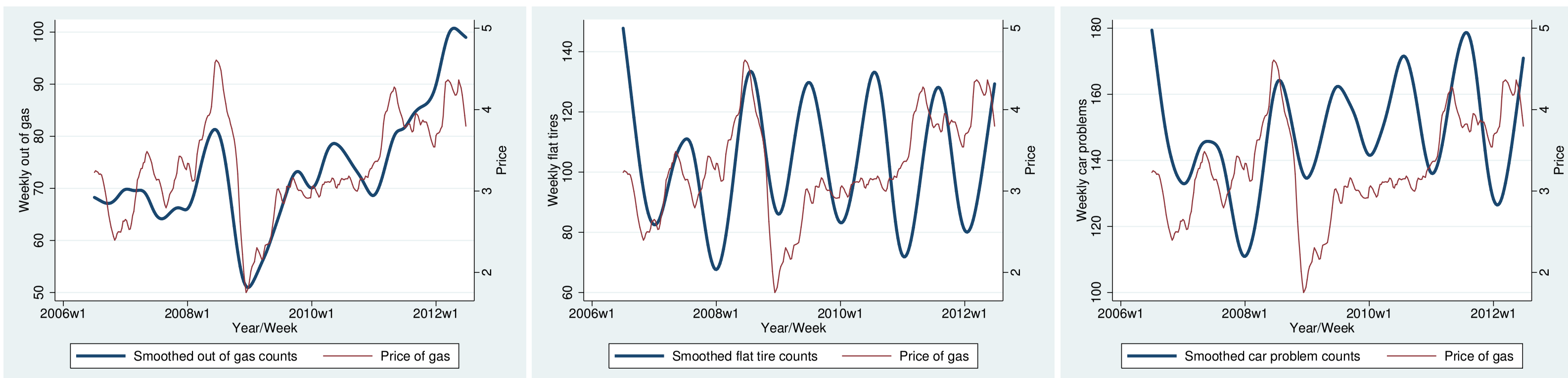

Figure 1.1: Gas-outs, flat tires, and car problems trend in District 3

Notes: Trends overlaid with the price of gas. Trends are smoothed using the HP-filter withs smoothing parameter 1600.

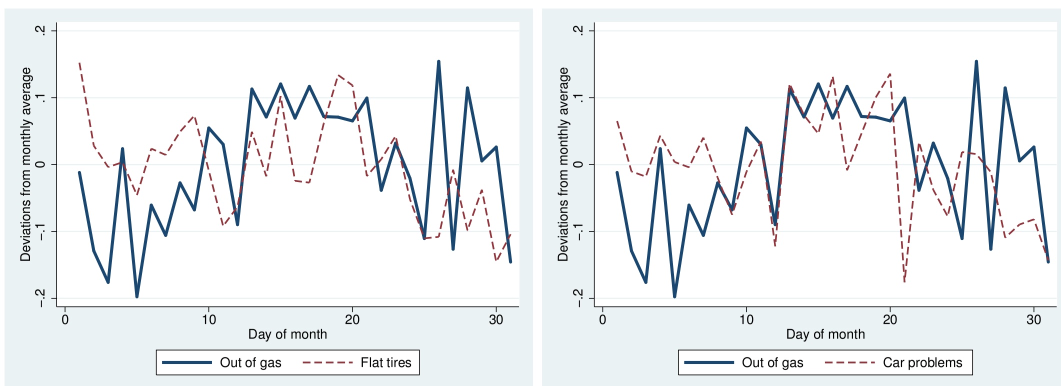

Figure 1.2: Monthly trends in gas-outs, flat tires, and car problems.

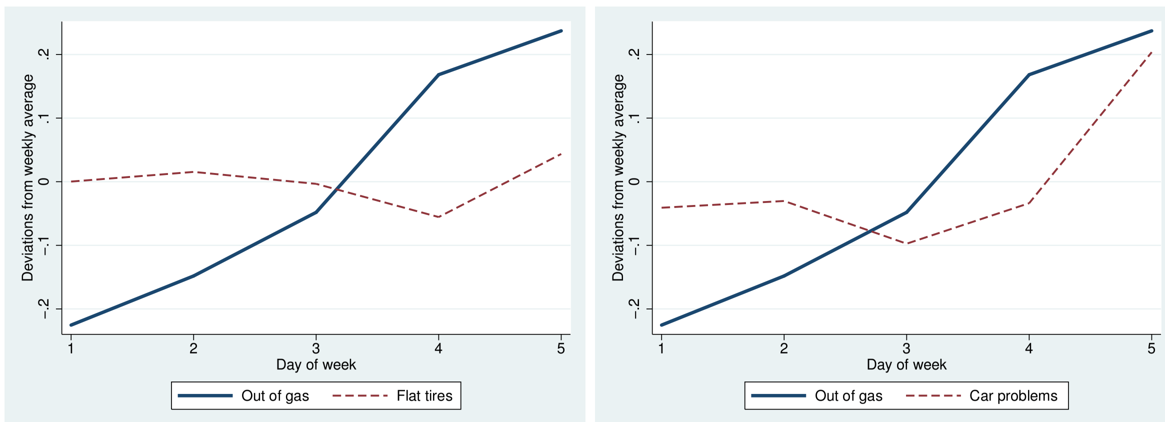

Figure 1.3: Day of week trends in gas-outs, flat tires, and car problems

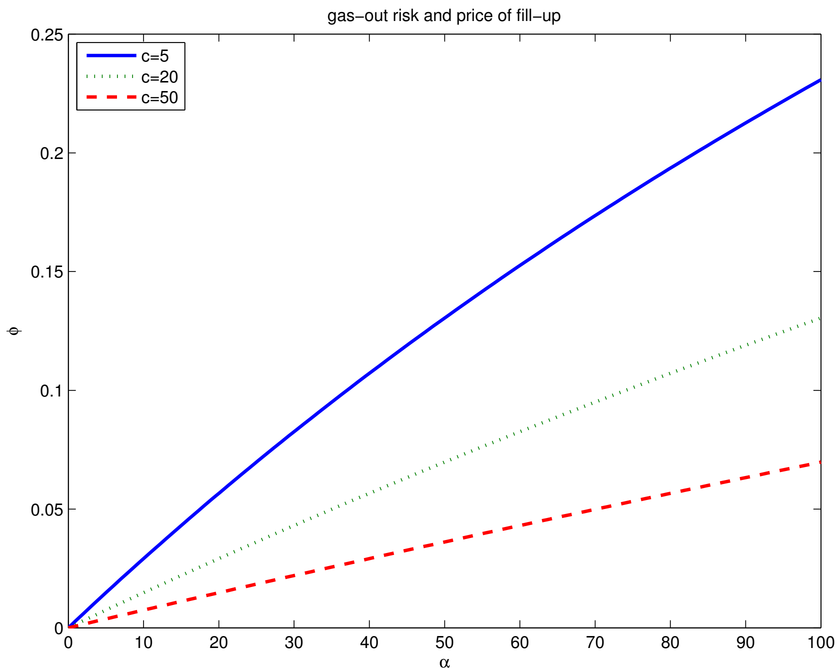

Figure 1.4: Threshold gas-out risk and fill-up cost
Notes: Callibrated to a value of $\delta\gamma = 0.97$.

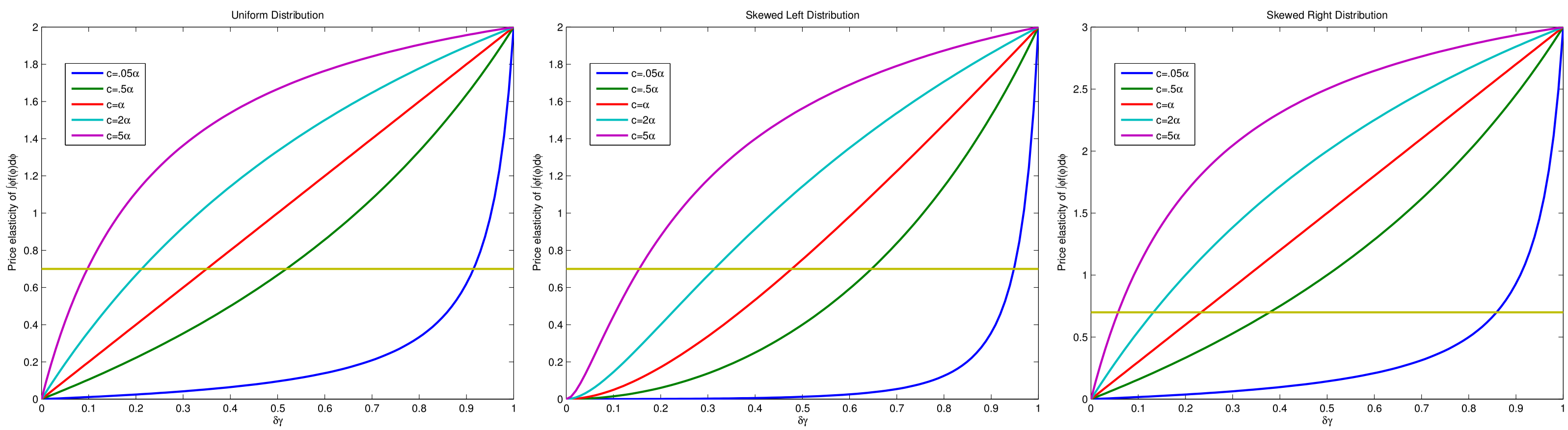

Figure 1.5: Can we get reasonable parameter values?

Notes: The horizontal line intersects the vertical axis at 0.7. Where this line hits the curves pins down a ratio of c/α and value for $\delta\gamma$ so that the model is consistent with the price elasticity of gas-outs we see in the data.

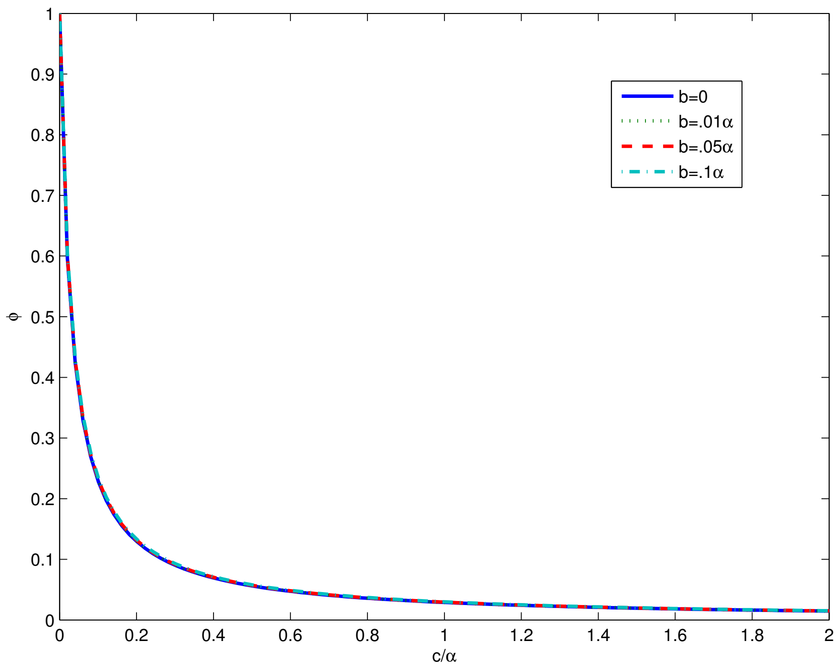

Figure 1.6: Threshold gas-out risk for the sophisticated type and the ratio c/α

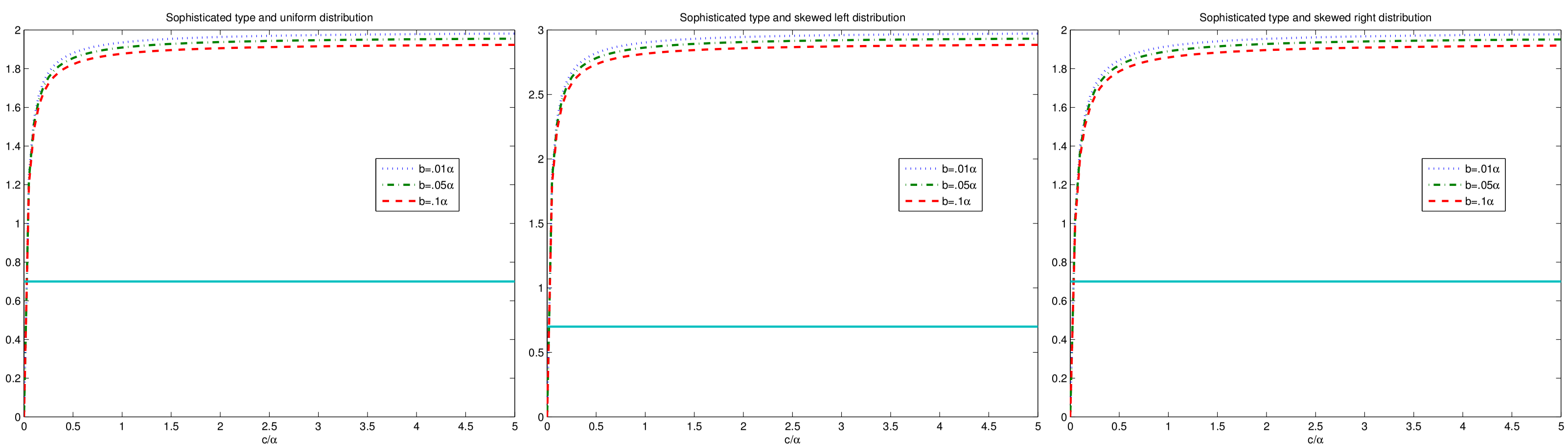

Figure 1.7: Sophisticated drivers price elasticity of gas-outs and the ratio c/α

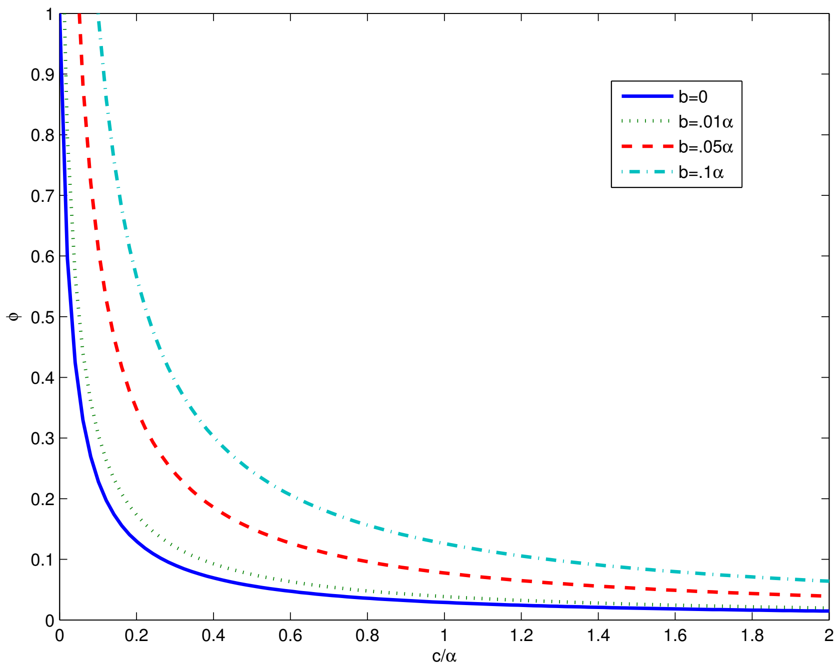

Figure 1.8: Threshold gas-out risk for the naive driver and the ratio c/α

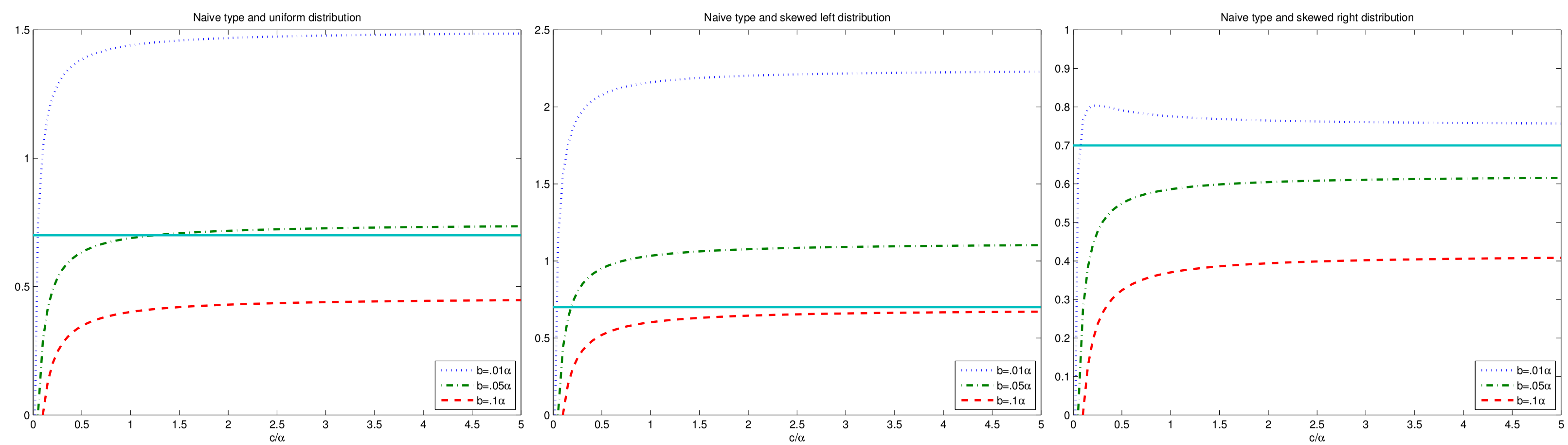

Figure 1.9: Naive drivers price elasticity of gas-outs and the ratio c/α

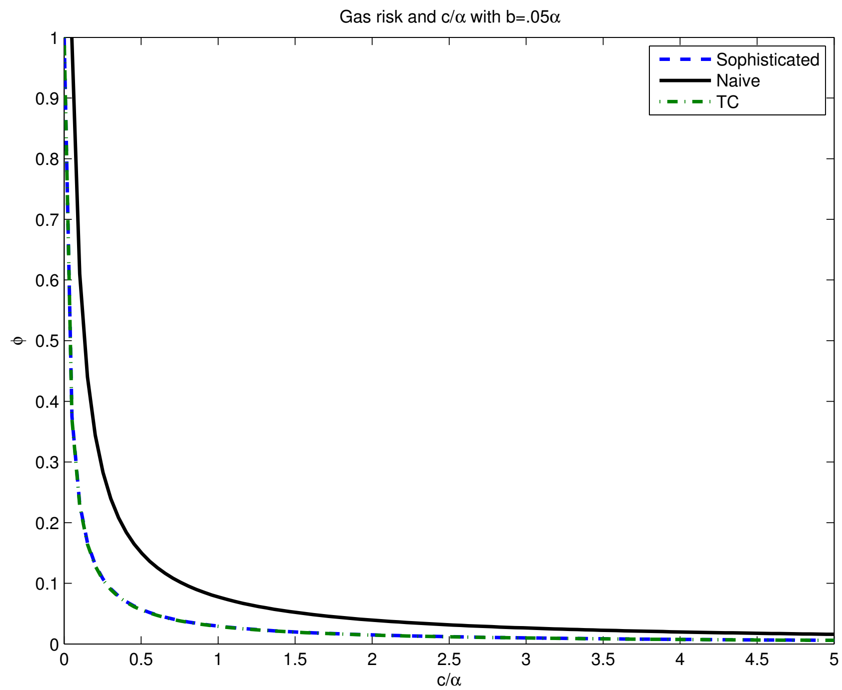

Figure 1.10: Threshold gas-out risk for time consistent, sophisticated, and naive drivers

Notes: The curves for the sophisticated and time consistent drivers are almost directly on top of each other.

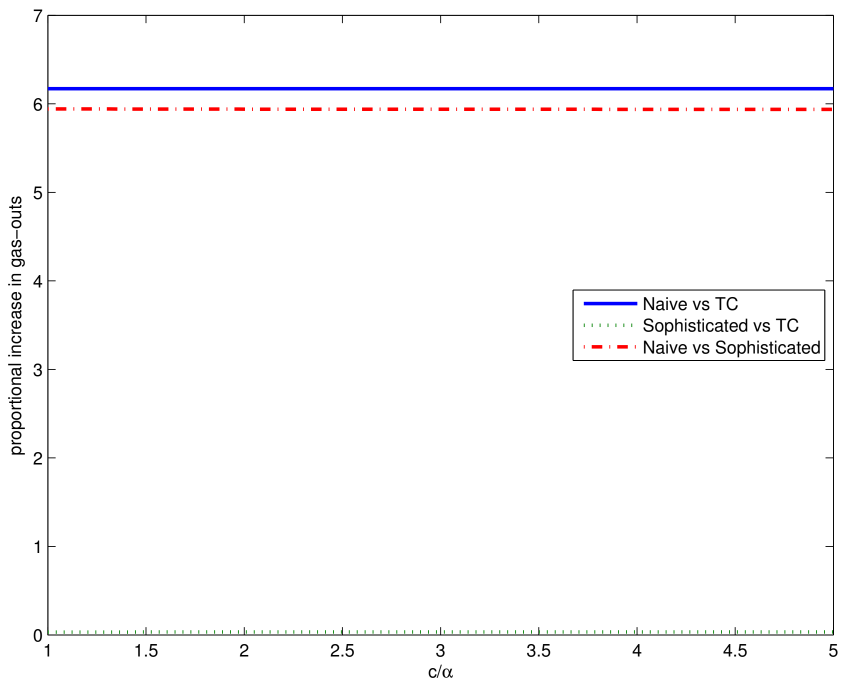

Figure 1.11: Differences in gas-outs due to driver type

Notes: Figure is calibrated for individuals with a discount factor $\delta = 0.99$, beliefs about tomorrows gas price $\gamma = .98$, and a behavioral cost of fill-up of $b = 0.05\alpha$.

Chapter 2

Switching and Sharing: Gasoline Prices and Household Fleet Utilization

2.1 Introduction

A husband commutes with his truck to the city while his wife drives her sedan to teach at the local school. However, when gasoline prices spike, both household members agree it would be better to swap work vehicles and postpone the weekend road trip. Stories like this are common. Households respond to increases in prices by demanding less. In the case of fuel use, households can decrease distance traveled or increase their fuel economy. This paper investigates behaviors such as this. I decompose short-run changes in fuel use into its components of distance traveled and fuel economy. Then, I examine explicit mechanisms through which distance traveled and fuel use can be adjusted in the short-run.

Consumer responses to gasoline prices are likely to be important. Gasoline use has ties to energy security, local and global pollution, traffic congestion, and traffic safety. Furthermore, the money spent on gasoline and time spent commuting makes gasoline use economically relevant even without its externalities. Because of this, there is a large literature estimating the effect of gasoline prices on fuel use and vehicle miles traveled.[1] However, the mechanisms that households use to adjust to gasoline prices in the short-run are not well understood.

Many studies assume that in the short-run, almost all changes in fuel use should be a result of decreases in distance driven and ignore the possibility of changes in short-run fuel economy.[2] These papers focus on the purchase of vehicles as the primary mechanism through which household miles per gallon (MPG) can change.[3] Those that do consider short-run changes in fuel economy have speculated that changes in driver behavior, such as adjustments in acceleration techniques (Gillingham, 2011), may be significant contributors.[4] Other studies have suggested changes

[1]See Dahl and Sterner (1991), Espey (1998), and Graham and Glaister (2002) for older surveys of the gasoline demand literature.

[2]For example, in simulations, West (2004) assumes only vehicle miles traveled is changed in the short-run as a response to a gasoline or miles traveled tax. If fuel economy is also something that is changing, this will change how we evaluate current tax policies.

[3]For example, Greene (1990) looks at the vehicle purchases and how they are affected by prices and policies such as taxes or CAFE standards . Li et al. (2012) use survey data to look at the effect of gas price on newly purchased vehicle MPG.

[4]Something that is related to driver behavior is vehicle speed. Austin (2008) shows individuals

in how household vehicles are utilized (Knittel and Sandler, 2013). Investigating short-run changes in travel behavior and understanding mechanisms households use to save fuel requires both household level data and observing behavior over a short time frame. Unfortunately, most studies do not have both these characteristics in their data. The previous two papers cited used very detailed data on vehicle utilization through California's smog check program. However, smog checks are relatively infrequent resulting in 2-year price elasticities instead of short-run responses to gasoline prices. Levin et al. (2015) uses high frequency data from credit card transactions that allows for short-run gasoline demand elasticities at the city level; however this doesn't give insight into what specific households are doing.

This paper addresses this gap in the understanding of short-run household responses to gasoline prices. A novel contribution is estimating how much of the decrease in short-run fuel use due to gasoline prices can be attributed to adjustments in distance traveled and how much can be attributed to adjustments in fuel economy. The MPG elasticity that I estimate comes from changes in vehicle utilization; households can adjust MPG in the short-run by allocating more miles to higher fuel economy vehicles and taking miles away from low MPG vehicles. This is different from past medium- or long-run MPG elasticities that estimate changes in household fuel economy due to the purchase of vehicles. It is also different from MPG changes coming from driver behavior such as conservative acceleration or driving slower on the freeway. I also estimate the effect of gasoline prices on explicit behaviors that households may take to increase fuel economy in the short-run. This highlights the interesting role that household interactions and the household fleet play in adjusting to gasoline prices.

I am able to identify short-run responses to gasoline prices using data from the National Household Travel Survey (NHTS). This survey contains detailed information on household characteristics, vehicle holdings, and typical travel patterns.

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may adjust their driving speed as a way to increase fuel economy both as a short-run and long-run strategy. However, Wolff (2014) provides evidence that this decrease speed is a result of a tradeoff between the time savings and extra fuel use from speeding. Speeding saves time but uses more gasoline.

Each household was also assigned a day to keep a 24-hour travel diary, recording data on length, purpose, and mode of transportation of each trip taken. As a result, the data contains detailed household level information and short-run behavior. Comparisons between actual travel day behavior and what might be expected given annual travel patterns of the household are the basis for the short-run gasoline price elasticities.

I find a short-run fuel use elasticity of -0.1, consistent with the prior literature. While much of the literature has assumed that almost all short-run decreases in fuel use come from decreases in VMT, I find that about 17 percent of the fuel use elasticity can be attributed to increases in average MPG. Heterogeneity in household characteristics are associated with different fuel use elasticities and decompositions. For households with more diverse vehicle fleets in terms of differences in vehicle MPG, 35 percent of the fuel use elasticity can be attributed to changes in fuel economy while households with homogenous fleets decrease fuel use almost entirely through decreases in driving. Poor households and rural households are found to be more responsive in decreasing fuel use than their wealthier or urban counterparts.

In terms of mechanisms, decreases in VMT do not appear to come from taking fewer trips but instead are more likely to come from shorter trips. I find that households are more likely to drive their most fuel efficient vehicles when gas prices are high. This behavior is observed both in trips taken alone and when household members take trips together. An individual is more likely to use another household member's vehicle on trips taken alone if that vehicle gets better gas milage. On shared trips, high prices induce household members to choose vehicles with better fuel economy.

These findings have several broad policy implications. The presence of short-run changes in MPG implies short-run changes in the weight of the overall vehicle fleet. Vehicle weight has been shown to have significant impacts on road safety due to traffic collisions. The results also suggest heterogeneity in households' ability to adapt to gasoline price shocks. A household's ability to adapt to gasoline price shocks is an important consideration for lenders in the housing market. The degree to which households can adjust MPG in the short-run is also important in assessing short-run effects of proposed policies to decrease driving such as gasoline or mileage taxes. The amount of intra-household switching may also allow us to learn more about about individual preferences. It may also inform us on how we should shape policy promoting alternative fuel vehicles.

The rest of the paper is organized as follows. Section 2.2 provides a description of the data. Section 2.3 discusses the estimation strategy for identifying the effect of gas price on fuel use, VMT, and MPG and provides the results from the decomposition. It then shows differences in these responses by household characteristics. Section 2.4 identifies ways that households change MPG in the short-run. Section 2.5 concludes and provides examples of possible extensions and policy applications.

2.2 Data

The primary source of data is the 2009 National Household Travel Survey (NHTS)[5]. The NHTS sample size was 150,147 households. For each household, information was collected on the household's characteristics, geographic location, and vehicle fleet. An important aspect of this survey is a 24-hour travel day where households kept a travel diary. Household members recorded the following information: time, length, purpose, and mode of transportation of each trip taken during the travel day. This also included data on which household vehicle was used and also information about other household members on the trip.

From the travel diary I am able to construct the main variables of interest: fuel use, VMT, and average MPG of each household on the travel day. VMT is calculated as the sum of all the household's VMT. Fuel use and average MPG are constructed using MPG data[6] specific to the vehicles make, model, and model year that is included in the NHTS data.

[5] US Department of Transportation, Federal Highway Administration (2009)

[6] Unadjusted 55/45 combined fuel economy.

I restrict my sample to households with at least two vehicles, since changes in MPG are not possible for single household vehicles. I also restrict my sample to households which reported VMT for all the vehicles in the household fleet. With these restrictions, my sample consists of 97,576 households surveyed between the dates of March 28, 2008 to April 30, 2009. For each household, I match the average retail price for a gallon of regular unleaded gasoline corresponding to their travel day.[7]

Table 2.1 provides summary statistics for my sample and compares them to population estimates from the NHTS dataset. The difference between the two columns reflect differences in household characteristics related to owning two vehicles versus owning at least one vehicle. The averages appear close for characteristics like persons per household and workers per household. The households in the restricted sample are on average larger, own more vehicles, have more drivers, and are wealthier. Households in the sample on average have fewer workers and are less likely to be classified as living in an urban environment.

The differences in households with one or more vehicles and two or more vehicles can most easily be seen in estimates of annual VMT. Household with two or more vehicles drove almost 10,000 more miles on average compared to the all households. However, controlling for the average number of vehicles indicates the sample households only drive each individual vehicle 317 more miles than an average household in the population.

The last two rows of the table show the difference between the average gas price and travel day characteristics during the sample period and a household-weighted average of gas prices and travel day characteristics. This shows that more households were surveyed when the gas prices were lower than average. This occurs because gas prices were high at the start of the sampling period, peaking around July 2008, and then decreased over the survey period, ending low. On the other hand, the number of households surveyed by month peaked in the middle of the

[7]The gasoline price does not vary by location in my main specification. In the robustness checks, I also impute monthly state level variation in gasoline prices based on state level average gasoline prices and state level gasoline taxes. The main results are robust to this adjustment.

sampling period.

Table 2.2 gives an overview of the types of vehicles these multi-vehicle households own. The table indicates that 79% of these households own at least one car, 19% own at least one van, 43% own at least one SUV, 47% own at least one pickup, and about 7% own a motorcycle. The table suggests that households often own vehicles with complementary uses. For example, households are not as likely to own multiple vans, SUVs, or pickups.

Finally, I provide evidence that looking at two vehicle households provides a sample that is economically relevant. Figure **??** shows estimates of the population's holding of vehicles by household income. It shows that the number of vehicles a household owns increases with income. However, there are multiple-vehicle households for all income levels of the population. Multiple vehicle households make up almost 20% of the poorest households. In the middle- to high-income categories, multiple vehicle households make up the majority of households.

2.3 Price and the response in fuel use, VMT, and MPG

In this section, I estimate the price elasticity of fuel use, VMT and MPG. I show there is heterogeneity in the price elasticity of fuel use and also in how it is decomposed into VMT and MPG. Finally, I present evidence of how VMT is decreased by looking at the number of trips households take and the average length of these trips.

2.3.1 Econometric Specification: Price and the response in fuel use, VMT, and MPG

To look at the effect of price on travel day behavior I adopt a common specification:

$$Y_{it} = \beta_0 + \beta_1 P_t + \beta_2 \hat{Y}_i + \gamma' S_t + \epsilon_{it} \tag{2.1}$$

where i indexes an individual household and t is a specific day of the year. Y_{it} is the dependent variable of interest summarizing a household's travel day behavior: fuel use, VMT, or average MPG. P_t is the price of gas on a household's travel day.

$\hat{Y}_i$ is a baseline measure for the dependent variable that measures a daily average fuel use, VMT, and MPG from a household's report of annual behavior and vehicle ownership. I use the NHTS variable *bestmile*[8], an estimate of the annual number of miles driven by each of the household vehicles, to construct these baseline measures. For the regression on VMT, this variable is bestmile divided by 365. For the regression on fuel use, $\hat{Y}$ is the household's annual fuel use as calculated as:

$$\frac{\sum_{j=1}^{J} bestmile_j \times MPG_j}{\sum_{j=1}^{J} bestmile_j} \tag{2.2}$$

where household i has a total of J vehicles and j is an index for each individual vehicle. For the average MPG regression, $\hat{Y}$ is the average MPG of all the household's vehicles. S_t is a vector of seasonal and time varying control variables.

The variable of interest is β_1, the effect of gas price on travel day behavior. One concern could be the presence of omitted variables. For example, Dahl and Sterner (1991), consider models not including income as mis-specified. Income is

[8]Bestmile is an estimate of the number of miles driven by each of the NHTS vehicles based on the best available data. This data includes vehicle related variables: an odometer reading, vehicle model year, vehicle type, and self reported annual miles. It also includes household related variables such as size of MSA of households, census division, household life cycle classification, household size, and household vehicle count. Finally it contains information on the vehicles primary driver including education, age, worker status, and sex. See *Developing a Best Estimate of Annual Vehicle Mileage for 2009 NHTS Vehicles, 2011* for more details.

likely to affect travel day VMT and will also affect how much a household drives in a given year. Similarly, geographic characteristics are likely to affect travel day VMT as well as household annual VMT. Bias on β_1 from an omitted variable, Z would take the form:

$$\frac{1}{K}[var(P)cov(P,Z) - cov(P,\hat{Y})cov(\hat{Y},Z) - cov(P,S)cov(S,Z)] \qquad (2.3)$$

I make the assumptions that (i) travel day gas price is uncorrelated with the omitted variable, (ii) travel day gas price is uncorrelated with the households annual vehicle use behavior, and (iii) the season of the travel day is uncorrelated with the omitted variable.

The first assumption, that travel day gas price is uncorrelated with any omitted variables, could be violated if the timing of the NHTS survey was correlated with household characteristics such as income. The NHTS survey was designed to yield an equal probability sample of household's with landline telephones with additional add-on areas. These were not targeted on certain days because of income but sampled from banks of telephone numbers that contained numbers with the first eight digits in common. It is unlikely that this sampling mechanism targeted household's based on characteristics that would be considered omitted variables in the model. The first assumption could also be violated if geographic characteristics were correlated with the gas price. For example gas prices in cities and rural areas differ. My data only contains a single gas price for all locations so that this is not a problem.

The second assumption, that travel day gas price is uncorrelated with the household annual vehicle use behavior, may be violated if the current gas price influences a household's report of last years behavior. Perhaps if the gas price is salient at the time of survey, a household may be more likely to over- or under-report behavior pertaining to driving. In the NHTS, drivers are asked to report annual miles driven for the past year. This is more likely to be affected by average prices over the last year than the price on the survey date. This appears to be true in a regression of bestmile on the travel day gas price and the average gas price over the last year. Travel day gas price is insignificant while the coefficient of average gas price is negative and statistically significant. The only other way vehicle level characteristics could be correlated with travel day prices is if the travel day price induced a household to go purchase a new vehicle on the travel day. I think this is unlikely but examine the posibility in the robustness checks. Results are similar when excluding vehicles purchased within six months of the travel day.

The final assumption, that season is uncorrelated with the omitted variables. will hold as long as the omitted variables in question are predetermined. This is likely to hold as well since major travel indicators are related to household geography or household characteristics that are difficult to change. Variables affecting travel day behavior such as weather are assumed to be captured in the seasonal time trends.

The inclusion of $\hat{Y}$ makes the estimating equation take a form similar to partial adjustment models of demand, such as Houthakker et al. (1974). One difference between my model and other partial adjustment models is the use of last year's behavior instead of yesterday's behavior. I interpret the β_1 as the effect of price on travel day behavior after controlling for what would be expected given the individual household's typical long-run behavior and the fact that a household's vehicle stock is fixed in the short-run. β_2 cannot be interpreted as the effect of a unit change in the baseline because things such as household and geographic characteristics affect both Y and $\hat{Y}$.

Seasonal controls are needed since driving behavior and gas prices are known to be correlated with the time of year. Excluding these would result in bias of β_1. One issue with the data is the short time frame. Because of this, high frequency time controls can explain the majority of the variation in gas prices. I find that controlling for seasonality with a polynomial or fixed effects more frequent than a monthly basis leads to unstable coefficients on all variables. There is a tradeoff between controlling for seasonality and retaining variation in gas prices. Because of this, I include bi-month dummies: Dec/Jan, Feb/March, etc... The results are similar when controlling for seasons using 12 individual month dummies or seasonal dummies for winter, spring, summer, and fall. I also include day of week indicators to control for weekly travel trends.

The coefficients on the seasonal controls can also be interpreted as the effect of that indicator on travel day driving behavior if we assume $cov(P,Z) = cov(S,Z) = cov(S,\hat{Y}) = 0$. The first two of these were already assumed for the unbiased estimate of β_1. The third covariance term says that the season is not correlated with bestmile. Since last year's travel behavior is predetermined, the assumption will not be violated unless something with the sampling was based on the season.

2.3.2 Results

Table 2.3 shows the results from the estimation of equation 2.1 with columns corresponding to fuel use, VMT, and MPG. Price has a negative and statistically significant effect on both fuel use and VMT, and a positive and statistically significant effect on travel day MPG. The statistically significant coefficients on the $\hat{Y}$ variables indicate that these baseline measures are highly correlated with actual behavior. The coefficients on the bi-month fixed effects indicate that both fuel use and driving are highest in the summer months of June and July and lowest in the winter, the omitted category of December and January. Travel day MPG does not appear to vary significantly with the time of year.

Table 2.3 shows that for households with two or more vehicles, the associated elasticity of gasoline use, VMT, and MPG are -0.107, -0.0868, and 0.0188 respectively. This MPG elasticity is novel in identifying short-run adjustments in fuel efficiency and has not been identified before in the literature. For each household, $Fuel\ Use = VMT/MPG$. Thus, these three elasticity estimates make up the parts of the fuel use decomposition. We should expect that the fuel use elasticity is equal to the VMT elasticity minus the MPG elasticity.[9] While it might have been

[9]The elasticity of a ratio is the difference between the two elasticities:

$$\frac{\partial(y_1/y_2)}{\partial x}\frac{x}{y_1/y_2} = \frac{\partial y_1}{\partial x}\frac{x}{y_1} - \frac{\partial y_2}{\partial x}\frac{x}{y_2}$$

possible to infer the MPG elasticity from a fuel use and VMT elasticity, I am able to estimate all three and make sure they are right. They indicate that on average, VMT makes up about 81% of the fuel use elasticity and about 17% comes from changes in MPG. If I include single vehicle households as well, the implied fuel use and VMT elasticities are -0.120 and -0.101 respectively. This indicates that multi-vehicle households are less responsive in terms of fuel demand. When including single vehicles households, decreases in VMT make up 85% of the decreases in fuel use. This increase in the proportion attributed to VMT comes from the fact that single vehicle households cannot increase fleet MPG.

The estimated elasticity of gasoline demand appears to be consistent with the existing literature. Dahl and Sterner (1991) indicate that when comparing demand elasticities, proper stratification of studies by model and data type are important to find a consensus. Their survey finds an average short run elasticity close to -0.26. However, the study finds an average elasticity of -0.13 when looking at cross sectional-time series data at a quarterly level, which is consistent with my findings. In more recent studies, Davis and Kilian (2011) use data ranging from 1989 to 2008 and find a short run elasticity in the range of -0.10 to -0.46. Park and Zhao (2010) estimate a short run elasticity of -0.15 using 2008 data. The fuel use elasticity in my paper is higher, but within the range of several other recent studies. Hughes et al. (2008) find a short run elasticity in the range of -0.034 to -0.077 during the time period of 2001 to 2006. Small and Van Dender (2007) estimate a short run elasticity of -0.0657 to -0.0873 using a pooled cross section of US states for 1966-2001. Several factors could possibly account for this difference. One factor is the difference in time periods analyzed. Gillingham (2013) looks at data in 2007-2008 and finds substantial responses to gas prices that were not present in past years.[10]

The degree of aggregation may also play a role in the slightly smaller estimates in Hughes et al. (2008) and Small and Van Dender (2007). Levin et al. (2015) use data from 2006 to 2009 and obtain a price elasticity ranging rom -0.29 to

[10]Gillingham (2013) finds a fuel demand elasticity of -0.22. This is larger than my estimates but is also a medium-run elasticity.

-0.61. They show that one possible reason why their estimate is higher than other recent estimates is data source and aggregation. While their dependent variable is city level quantity of fuel purchased per capita, I use an even more disaggregate dependent variable, household level gasoline use. One possible explanation for the difference between our estimates could be the difference in gasoline purchases versus gasoline use. Since people can hold inventories of gas in the short run, households may be able to respond more elastically to gas purchases than they would to actual fuel use.

The VMT elasticity is also in line with historical estimates. These range from about -0.05 to -0.23. Many lie in the range of about -0.1. See for example Austin (2008).

The short-run elasticity of MPG that I estimate comes from changes in the allocation of driving in the household fleet. To my knowledge, there has been no previous estimate of this. When MPG is considered in the literature, the focus is on MPG of purchased vehicles. This ranges from 0.001 to 0.21. For example, Klier and Linn (2010) finds an estimate of 0.12. For many households, there is little room to respond. Bento et al. (2009) are able to uncover a 1-year MPG elasticity and find that changes in MPG make up only about 1% of changes in gasoline use. Their findings suggest that over ten years only three percent of gasoline use decreases will come from increases in MPG. My results counter this by suggesting that even in the very short run households are much more responsive on the margins of MPG.

This decomposition is similar in spirit to Archibald and Gillingham (1981). The authors of this paper use household level data from the 1972-73 Consumer Expenditure Survey and find that 22 to 29 percent of the fuel use elasticity can be attributed to changes in fuel efficiency. Unfortunately, only one of their estimates is statistically significant. Surprisingly, they find that 22 percent of the response to prices in single vehicle households comes from increases in fuel efficiency. Kayser (2000), is a more recent paper that tries to link household level gasoline demand and VMT in the short-run. This paper calculates gasoline demand by dividing reported miles traveled by an imputed household-specific MPG. It finds a short-run price elasticity of gasoline demand -.023 and a positive but statistically insignificant price elasticity of VMT. The author argues that this implies the majority of short-run changes to fuel use occur through changes in vehicle utilization. My paper, that does not impute MPG data, counters this, suggesting that the majority of decreases in fuel use come from decreases in VMT.

Both of these two papers rely on a dependent variable that is measured with error. The first deflates gasoline expenditures by average gasoline prices over a specific time period to estimate gasoline demand. The second uses a more complex procedure to impute predicted fuel economy using household characteristics and a secondary data source. My paper improves on both these methods by calculating actual travel day MPG and providing precise estimates for each elasticity of the decomposition. In these papers, the gasoline price doesn't vary by time but instead is a constant average gasoline price by region. Instead, my paper utilizes substantial variation in gasoline prices by using daily price data allowing for more precise estimates and a closer look at short-run behavior. Finally, my estimation method compares household deviations from a benchmark instead of comparing these benchmarks across households. This allows for more precise estimates with fewer regressor, many of which might be endogenous.

2.3.3 Heterogeneity by household characteristics

Vehicle Fleet

Households can only change their MPG to the point their fleet allows them to. To look at the effect vehicle fleet can have on the price elasticity of fuel use, VMT, and MPG, I construct a variable measuring the difference in MPG between a household's minimum and maximum fuel economy vehicles. I split the sample equally by this measure.

Households below 50th percentile of this measure have an average difference of 3.69 MPG between their minimum and maximum MPG vehicles, with a range from 0 to 7.5 MPG. I refer to these households as having homogenous fleets. The distribution of differences in MPG is spread uniformly among these households. Households above the 50th percentile have an average difference of 17.81 between their minimum and maximum MPG vehicles with a range above 7.5 to 110 MPG. I refer to these households as having heterogenous fleets.[11]

Table 2.4 shows the result of separately estimating equation (2.1) for homogenous and heterogenous fleets. The decomposition of fuel use into VMT and MPG is very different for these two types of households. For households with homogenous fleets, changes in fuel use come almost entirely, 99%, from changes in VMT. On the other hand, households with heterogenous fleets can decrease fuel use on both the VMT and MPG margins. For these households, more than a third of the decreases in fuel use come from changes in MPG and about 60% of the decrease in fuel use comes from decreases in driving. Both types of households appear to have a similar price elasticity of fuel use, with the response perhaps being slightly larger for households with homogenous fleets. This could be because households with heterogenous fleets can save fuel in a less costly manner and will therefore have a more inelastic elasticity of fuel demand.

Income

Income is an important determinant of travel behavior that is not included in equation (2.1). Income is not included because it could be an endogenous regressor; income is correlated both with travel day behavior as well as the annual VMT. Here, I divide my sample into two income categories: households with incomes less than twice the 2009 poverty rate and households with incomes greater than twice the 2009 poverty rate, controlling for the household size.[12]

Table 2.5 shows the result of estimating equation (2.1) with these two samples. Comparing the constants and seasonal indicators shows that wealthier house-

[11]The distribution of differences for these households is skewed to the right. At the 99th percentile, the largest difference is 48.17 MPG. Households with these large MPG differences either are the owners of electric vehicles. I also run all regressions dropping vehicles with fuel economy greater than 60 MPG and the results are the same. The results are not driven by these households.

[12]According to National Center for Children in Poverty, families typically need an income of at least twice the official poverty level to meet basic needs. Cauthen and Fass (2008)

holds on average have higher VMT than poorer households. The main difference between these two groups is the price elasticity of fuel use is twice as large for poorer households. There also appear to be slight differences in how this decrease is achieved with proportionally more of the decrease in fuel use coming from decreases in VMT in poor households. This may reflect wealthier households having more diverse vehicle fleets.

These results are in line with previous studies that show low income households are more responsive than higher income households. For example, West (2004) finds households in the lowest expenditure decile have over a 50% greater responsiveness to gasoline price than households in the highest expenditure decile. I find that low income households are about twice as responsive as other households in fuel use and more than twice as responsive in terms of VMT. Some studies have found that the highest income households are also very responsive to gas prices resulting in a U-shaped response to prices by income. This could be due to these households having a lot of discretionary driving. I also estimate the price elasticities for the highest income households but find that if anything, they are less responsive. These results are not reported.

Urban and Rural Households

I also examine heterogeneity in geography. Understanding the effects of gas prices by location can help inform policy targeting local air pollution and congestion. I use a broad definition of geography by differentiating only by urban and rural areas. Table 2.6 shows the results of estimating (2.1) with the sample split by household dwelling location. Looking at the constant and bi-month fixed effects indicates that rural areas are associated with more fuel use and more driving. This is not surprising since urban areas are more likely to have better access to public transportation and be more compact. I find that rural households have a larger price elasticity of fuel use than urban households. This is reflected in a higher VMT elasticity and a higher MPG elasticity. Rural households also decrease VMT proportionally more than urban households.

This result is not in line with some studies looking at urban and rural differences. For example, Wadud et al. (2010) find higher responsiveness for consumers in urban areas rather than rural areas. This paper used state variation in gasoline prices. One explanation could be that gas prices are typically higher in urban areas. Higher responsiveness can be picking up differential responses to prices. Perhaps higher gas prices in cities are more salient. However, my results are consistent with findings in Gillingham (2011) who finds consumers in more densely populated areas are less responsive.

2.3.4 Stops

Changes in VMT can be further decomposed into number of stops and the distance per stop. One question of interest is whether high gas prices decrease VMT through households limiting the activities that they use household vehicles for, or whether the decrease in VMT comes from changes in the distances households are willing to travel. I provide preliminary evidence that households do not limit the use of their vehicles but instead take shorter trips.

The two variables of interest for this are the number of stops a household takes in a household owned vehicle and the average distance a household travels per stop. I estimate regressions in the form of equation (2.1) with $\hat{Y}$ being the estimate annual VMT.

Table 2.7 shows the results from these regressions. The first column indicates that price does not have a significant effect on the number of stops a household takes. The coefficient would suggest that if anything, households take more trips when the gas price is high. The second column indicates that price has a negative and significant effect on the distance households travel between stops. This suggest that households are more likely to travel to closer destinations when the gas price is high.

2.4 Mechanisms for changing MPG

Previous work looking at MPG elasticities have focused on MPG of new or newly purchased vehicles. Changes in short-run MPG that do not stem from purchasing vehicles have been attributed to changes in driving behavior such as accelerating more slowly or reallocation between city and highway driving. My approach is to look at changes in vehicle utilization. After controlling for average fleet fuel economy, changes in MPG would be due to differences in the allocation of VMT among the household vehicle fleet. This section identifies several behaviors households may take and looks at the effect of gasoline prices.

2.4.1 Vehicle Utlization

A simple response to gas prices could be to use the highest MPG vehicle more and the lowest MPG vehicle less. To look at the effect of price on this type of behavior, I construct several indicator variables of vehicle utilization. These are: whether a household used its highest MPG vehicle at all, whether a household used its highest MPG the most, and the same indicators but for the lowest MPG vehicle.

I assume that households begin a travel day with a set of fixed household characteristics and with a set of day specific characteristics. These characteristics affect the household's vehicle utilization choices. For example, larger households may be more likely to use the low fuel economy vehicles if they need space to transport multiple people. The day specific characteristics can be manifested as travel needs such as going to work or dropping a child off at school. For example, a parent may want to take a larger (low MPG) vehicle when dropping kids off at school because the vehicle will be roomier and may provide greater safety to its occupants. The day specific characteristics also include the price of gasoline as this may induce households to shift driving to the more fuel efficient vehicle.

I model the effect of these characteristics on vehicle utilization choices by running a logit regression of the form:

$$Pr[Y_{it} = 1|X] = \frac{exp(\beta_0 + \beta_1 P_t + \gamma' X_{it})}{1 + exp(\beta_0 + \beta_1 P_t + \gamma' X_{it})} \tag{2.4}$$

for each of the dependent variables discussed above. P_t is the price of gasoline and X_{it} is a vector of households and travel day characteristics. For travel day needs, I include controls for the number of trips originating from home by trip category. The categories are work, school/religious, medical/dental, shopping, social, family, transporting someone, meals, and other. Including these variables also controls for the number of trips the household needed to make during its travel day. I also include day of week fixed effects in the travel day characteristics. The household characteristics I control for are the estimate of annual VMT of the lowest and highest MPG vehicles, the difference between these fuel economies, the number of vehicles, and the household size.

Table 2.8 contains the results of the logit regressions looking at utilization of the low and high MPG vehicles. Columns 1 and 2 show the effects on whether or not the highest or lowest MPG vehicle was used at all. The first column implies that a dollar increase in the gas price is associated with a statistically significant 1.24 percentage point increase in the probability that a household drives their highest MPG vehicle. This coefficient represents a 1.83% increase over the average probability of driving the high MPG vehicle (67.59%). The second column implies a dollar increase in the gas price is associated with a 1.03 percentage point decrease the probability of using the lowest MPG vehicle. This represents a 1.69% decrease over the average probability of driving the low MPG vehicle (60.65%).

The trip purpose controls are all positive and significant. They indicate that the more trips are taken, the more likely households are to take any vehicle. The number of vehicles a household has makes them less likely to drive either the low or high MPG vehicles. This makes sense intuitively since having more vehicles to choose from makes it less likely that a specific vehicle will be chosen. Finally, the household size variable shows that large households are less likely to drive the highest MPG vehicle and small households are more likely to drive the lowest MPG vehicle. For the most part, high MPG vehicles are smaller. If there is a need to transport multiple family members, it is more likely this will occur in the larger vehicle.

Columns 3 and 4 of table 2.8 show that prices not only have an effect on which vehicles are used but how much they are used. Column 3 implies that a dollar increase in the gas price is associated with a 1.06 percentage point increase in the probability that the highest MPG vehicle was used the most. This represents a 2.59% increase over the average probability of this behavior (40.94%). Column 4 implies a dollar increase in the gas price is associated with a 0.93 percentage point decrease in the probability of using the lowest MPG vehicle the most. This represents a 2.68% decrease over the average probability of this behavior (34.89%).

I also construct a continuous measure of efficient fuel use, EFU. EFU takes the value of 1 if all the households travel day VMT occurred in the highest MPG vehicle and a value of 0 if all the households VMT occurred in the lowest MPG vehicle. Specifically,

$$EFU_{it} = \frac{MPG_{it} - minMPG_i}{maxMPG_i - minMPG_i} \tag{2.5}$$

where $minMPG_i$ and $maxMPG_j$ are the fuel economies of the least and most fuel efficient vehicles in household i's fleet. I interpret this as a measure of how hard a household tries in using its fleet efficiently. I use the same explanatory variables to look at the effect of price on EFU. Since EFU is a continuous variable, I estimate the effects using OLS.[13] Column 5 summarizes what is shown in the previous four columns using the EFU variable. It indicates that a 10% increase in the gas price is associated with a 0.69% increase in the EFU measure.

The similarities between the increase and decreases of vehicle utilization indicate that the miles that were driven by the lowest MPG vehicle are reallocated to the highest MPG vehicles when the gas price is higher. These results support

[13] I have also run this as a fractional logit (Papke and Wooldridge, 1996) and results are similar.

Knittel and Sandler (2013) who find some evidence that households change how they drive their vehicle fleet due to gas prices. The authors are able to match smog check data for a sample of their vehicles to other household owned vehicles. Conditional on owning another lower or higher MPG vehicle, they look at the relationship of average gasoline price between smog checks on the amount the tested vehicle is driven. They find evidence that price has an additional negative effect on VMT of vehicles if there is a higher MPG vehicle in the household and a positive effect on VMT if a household owns a lower MPG vehicle. This suggests that households with multiple vehicles shift driving from the lower MPG vehicle to the higher MPG vehicle. However, they are unable to tell whether or not these effects counteract each other. The results I have presented in section 2.3 indicate that these changes in vehicle utilization do translate into less fuel use overall.

2.4.2 Switching and Sharing

An interesting question that still remains is how VMT is reallocated among vehicles. I provide evidence of two possibilities: vehicle switching for single person trips and vehicle sharing for multiple person trips.

Imagine a household with two drivers and two vehicles. Assume each person takes his or her own personal vehicle to work and it just happens to be the case that the driver with the less fuel efficient vehicle works farther away. In order to save on fuel costs, these household members may be induced to swap vehicles when going to work if gas prices are high enough. I refer to this type of behavior as switching. Sharing behavior occurs when two or more drivers in a household take a trip in a single vehicle. High gas prices may induce drivers to take the more fuel efficient vehicle on shared trips, perhaps despite preferences for taking a larger vehicle.

I construct an indicator variable for whether a household exhibits switching or sharing behavior on its travel day. For switching to be possible, I require that a household have at least two drivers, at least two vehicles, and at least one of the vehicles must have a primary driver. For these households, I declare a switch has occurs if on a travel day trip: the driver of the vehicle is not the primary driver of the vehicle, the driver is the only person in the vehicle, and the trip started from the drivers home. The second condition excludes the possibility that the primary driver is also in the vehicle. The third condition makes it unlikely that the primary driver will be in the vehicle at a latter stage of the trip. Similarly, I limit sharing behavior to households with at least two drivers and two vehicles. I define a household having a shared trip if two or more drivers in a household start a trip from home in the same vehicle. Like the case of switching, I differentiate between whether or not the highest or lowest MPG vehicle was chosen.

To see if households are making more fuel efficient travel decisions, it is also important to know whether the switch would be advantageous or not. I identify whether or not a household member switched to the most fuel efficient vehicle and whether or not a household member switched to the least fuel efficient vehicle. Households where the lowest and highest MPG are the same are dropped.[14]

I assume the household's decision of whether or not to switch or share vehicles is similar to the choice of vehicle utilization discussed in the previous section. Because of this, I find it appropriate to estimate the same logit regression as equation (2.4) but with the indicator variables just discussed.

Table 2.9 reports the results of the logit regression for the indicators of switching behavior. While price does not have a significant effect on switching behavior or switching to the lowest MPG vehicle, it does have a positive and significant effect on switching to the highest MPG vehicle. Column 2 indicates that a dollar increase in price is associated with a 0.23 percentage point increase in the probability of switching to the highest MPG vehicle. This represents a 5.20% increase over the average probability of this kind of behavior (4.58%). There is an asymmetry in switching behavior and gasoline price. As indicated by column 3, lower gas prices are not associated with a statistically significant switch to lower MPG vehicles and the point estimate of the coefficient is less than half that of column 2. I suspect that this is because there is little incentive to change the status quo when prices are low. An individual's primary vehicle could be his or her preferred one. Column 2

[14]Results are similar if these households are not dropped

shows that households that utilize the most fuel efficient vehicle a lot already are less likely to have a switch to that vehicle. These household are also the most likely to already have allocated the most driving to the most fuel efficient vehicle.

Table 2.10 reports the results of the the logit regression for the indicators of sharing behavior. Price does not have a significant effect on the probability of a household taking a shared trip. However, price does have a positive statistically significant effect on shared trips in the highest MPG vehicle and a negative and statistically significant effect on shared trips in the lowest MPG vehicle. Column 2 indicates that a dollar increase in gas price is associated with a 0.2 percentage point increase in the probability of a household taking a shared trip in the highest MPG vehicle. This represents a 1.5% increase over the average probability of this kind of behavior (13%). Similarly, a dollar increase in the gas price is associated with a 0.3 percentage point decrease in the probability of sharing the lowest MPG vehicle, a 2.7% decrease over the average probability of this behavior (11%). Sharing behavior does appear to show symmetric movement with price. In this case, there might not be any status quo for which vehicle to take. Instead, this could be explained by a tradeoff households take between comfort of having more space on shared trips versus the increased cost of travel.

The trip purpose controls (not reported) indicate that household members are less likely to share vehicles when going to work. Every other activity is more likely to occur with another driver in the vehicle. Sharing is more likely to occur in households with more vehicles, however the sharing is less likely to occur in the lowest or highest MPG vehicle. Large households are more likely to share vehicles. For these households, sharing is more likely to occur in the low MPG vehicle and less likely to occur in the high MPG vehicle. This could be because low MPG vehicles have a greater passenger capacity. Households that drive their low MPG vehicle the most have fewer shared trips and are less likely to share vehicles on any trip. Interestingly, this is somewhat similar to the type of switching behavior seen in households that drive their low MPG vehicles a lot. This could perhaps be evidence of some sort of demand for driving or preference for large vehicles that these types of households have.

Morency (2007) has shown that sharing, a type of intra-household carpooling, has ambiguous environmental gains due to many trips being akin to one household member taxiing another household member. Behaviors that involve driving to a location to drop someone off and then immediately returning home generate double the vehicle trips had the individual just taken their own vehicle. These types of trips are most common among households with children. By restricting sharing behavior to drivers only, I partially address this issue. However, the main point of looking at sharing behavior is not counting the number of sharing trips, but it is to analyze vehicle choice. Holding the number of trips constant, taking the more fuel efficient vehicle will always result in lower fuel use.

2.4.3 Fleet Heterogeneity

Considering the effect of fleet heterogeneity is especially interesting when considering vehicle utilization. Households with more diverse fleets can save more by adjusting their driving patterns. At the same time, these vehicles will differ more in terms of other characteristics such as size and comfort level, perhaps making a switch more inconvenient. Table 2.11 shows the differences in vehicle utilization when looking at households with heterogenous fleets versus households with homogenous fleets. (Again, the cut point is 7.5 mpg). Homogenous fleet households still appear to make a small effort, but it appears that the households with more to save are more responsive to prices. Households with homogenous fleets have an EFU price elasticity of 0.0445 while households with heterogeneous fleets have an EFU price elasticity that is roughly double, 0.0900.

2.5 Discussion

Short-run responses to gasoline prices have important implications for policy. Below, I discuss several applications.

2.5.1 Safety

There is a large traffic safety literature looking at the relationship between average vehicle weight and traffic fatality rates. More recent work has looked at the role of fleet heterogeneity on safety, pointing out that decreasing total fleet weight does not necessarily affect the fatality rate. Instead, a main consideration should be how the distribution of heavy and light vehicles change (Anderson and Auffhammer (2014), Jacobsen (2013)). These papers attribute changing vehicle fleet to purchasing behavior. Thus, the types of new vehicles that enter the fleet are affected by policies such as taxes that increase the cost of heavier, low fuel economy vehicles, and policies that affect the vehicles available for purchase (i.e. CAFE standards). Anderson and Auffhammer (2014) estimate that a 4.5 MPG decrease is associated with a 1,000 pound increase in vehicle weight. Thus, my result that MPG is responsive to the gas price even without the purchases of new vehicles indicates the presence of short run changes in the weight of the vehicle fleet.

To explore this further, I look at how vehicle weight and the distribution of vehicle types on the road changes with gasoline prices. The data for weight comes from the National Automotive Sampling Systems Crashworthiness Data System (NASS-CDS) and Wards. For each make, model, and model year I have data on median curb weight. I am able to match weight data to 83% of household vehicles, (257,806 out of 309,163 vehicles). Vehicles that were not matched are primarily older vehicles. The NASS-CDS data only goes back to model year 1995 and the Wards data extends to 1988. 103,865 households have complete data on weight for each owned vehicle.

To explore the effect of price on vehicle weight, I consider two dependent variables: the average weight of vehicles used on the travel day and travel day pound miles traveled. The average weight of vehicles used on the travel day is calculated by adding up the weight of each vehicle that had positive VMT on the travel day and dividing by the total number of vehicles that had positive VMT on the travel day. Specifically, for each household, $avg\ weight = \sum_{j=1}^{J} weight_j/J$, where J is the total number of vehicles that had positive VMT and j indexes each individual vehicle.

Pound miles traveled for each household is calculated as $PMT_{it} = \sum_{j=1}^{J} VMT_j \times weight_j$. The estimation strategy is the same as discussed in equation (2.1), with the baseline measure being the average weight of the households vehicle fleet and average annual pound miles traveled.

Table 2.12 shows the results of regressions on pound miles traveled and average vehicle weight on travel day. It indicates that a dollar increase in the price of gasoline is associated with a decrease of 9,917 pound-miles traveled per household. This represents an elasticity of -0.142. This is larger in magnitude than the VMT elasticity, suggesting that the decrease in VMT is coming from more heavy vehicles than a random draw of the population would suggest. The second column indicates that a dollar increase in the price of gasoline is associated with a 19 pound decrease in vehicles used on the travel day per household. Although this does not seem to be a large number, the actual effect on weight should be added up over all households with 2 or more vehicles. This effect is driven by households with diverse vehicle weights. When run on a subsample of households with above average differences in maximum and minimum vehicle weight, a dollar increase in the price of gasoline is associated with a 30 pound decrease in the average travel day vehicle weight. These correspond to a short-run 0.5 to 1 percent decrease in fleet weight just through a dollar increase in price.

To look at what this means for the distribution of vehicles, I estimate equation (2.1) separately for different vehicle types, with the dependent variable being VMT. Table 2.13 shows the breakdown of the VMT elasticity by vehicle type. Increases in price are associated with decreases in VMT of vans, SUVs, and pickups. These are also the vehicles that, on average, weigh the most. Price doesn't have a statistically significant effect on the VMT of cars, however, the associated price coefficient is positive. This suggests that while some car owners may decrease their driving, other households switch from driving larger cars to driving their small cars more often. High prices are also associated with large and statistically significant increases in motorcycle VMT.

Overall, these tables suggest a short-run reduction in the weight of the fleet on the road. Decreases in weight are coming primarily from heavy vehicles so that the standard deviation of the weight of vehicles is decreasing. Anderson and Auffhammer (2014) show that distribution shifts that decrease mean and standard deviation of fleet weight result in fewer fatalities. The large shift to motorcycles does create more variance in the lower weights. Interestingly, the summer of 2008 marked the peak of the trend of rising gas prices that started in the early 2000s. This coincided with the largest number of motorcycle fatalities in recent years. Motorcycle fatalities rose steadily from 3,714 deaths in 2003 to 5,312 deaths in 2008 and decreased to the mid-4000's in the ensuing years.[15]

2.5.2 Gasoline shocks and the housing crisis

Recent work has suggested that rising gas prices played a role in triggering the housing market collapse. Sexton et al. (2012) argue that low gas prices pre-2000 coupled with a generous housing stock, federal policies, and low interest rates made homeownership in suburban areas an attractive alternative to renting in urban areas. This was especially true for lower income households that would typically be priced out of the urban market. However, rising gas prices during 2005 to 2008 disproportionately affected suburban and exurban areas because high commute costs lowered home values and also made them less affordable to those living there. The gas price shock in 2008 meant some of these households could no longer meet mortgage obligations.

My analysis supports this hypothesis. I run similar analysis decomposing the fuel use elasticity by distance to work and find that households with a oneway commute between 0 to 10 miles have a fuel use elasticity of -0.074, households with a commute of 10 to 20 miles have a fuel use elasticity of -0.18 and households with a commute of longer than 20 miles have a fuel use elasticity of -0.040.[16] Due to a reduced sample size, the estimates for short and long commute households are not

[15] Traffic Safety Facts, NHTSA (May 2014). DOT HS 812 016
[16] Details in appendix.

statistically significant and the estimate for medium commute length households is marginally significant.[17] The point estimates suggest that households that have the farthest commutes respond the least to gasoline prices in terms of fuel use. This could be because of the time costs or other difficulties associated with finding alternative transportation to work. Households with short commutes also do not appear to have a significant response to gasoline prices. This may reflect the fact that increasing gasoline costs may have only a small effect on these households. Households with a medium length commute appear to the the ones with enough incentives and feasible methods to decrease fuel use.

These results suggest that households living far from work are the ones hit hardest by a gas price shock. They use the most gasoline and adjust their fuel use the least. When considering the effect of a gas price shock, household fleet heterogeneity is perhaps an important measure of how much these households can absorb shocks. To explore how fleet heterogeneity plays a role in the ability to absorb gasoline price shocks, I decompose the fuel use response for households with a oneway commute of 20 miles or more and look at differences in these households. It appears as if households with heterogenous fleets are able to make decreases in fuel use that are almost an order of magnitude larger than households with homogenous fleets. Furthermore, the majority of the fuel use decrease for heterogenous fleet households appears to be coming from increases in MPG. The point estimate on fuel use suggests that households with heterogeneous fleets would use 0.08 fewer gallons per day if gas prices increased by a dollar. This adds up to about 2.5 gallons of fuel a month.

I explore what can actually be saved due to fleet heterogeneity by constructing a measure of optimal travel day MPG for each household that I then compare to average travel day MPG. Details of this measure can be found in the appendix. Differences between optimal MPG and average MPG indicate how much a household can save just through the reallocation of driving among vehicles. I find that 41% of

[17] I have also run this with distance to work and a quadratic of distance to work interacted with gasoline price. The negative coefficient on squared distance to work also imply the same relationship between distance to work.

households with oneway commutes greater than 20 miles allocated VMT optimally. When looking at the remaining 59% of households, those with homogenous fleets had a median fuel economy of 24.9 MPG with a median possible gain of 3.77 MPG per day. Households with heterogenous fleets had a median fuel economy of 22.6 MPG but had a median possible gain of 10.22 MPG per day. The median distance to work for these households is 32 miles. Thus, if the travel day MPG reflected the households typical behavior, the median household with a homogenous fleet could save 7.45 gallons a month through reallocation of VMT while a household with a heterogenous fleet could save 19.43 gallons a month through the reallocation of VMT. At the peak of the 2008 gasoline prices, households with diverse fleets and long commutes could save over 50 dollars a month more than households with long commutes and homogenous fleets.

Households with heterogenous fleets are are able to absorb a significantly larger proportion of gasoline price shocks. In the context of the housing crisis, households can easily fall behind mortgage payments by small amounts. Households are generally not good at predicting or accounting for gasoline price shocks. If they don't have flexibility to adjust fuel usage by switching or sharing, these un-budgeted expenditures can affect their ability to make mortgage payments. This is especially relevant in the context of adjustable rate mortgages that start with a lower interest rate in the first few years but then increase to much higher rates at a later period. Whether potential borrowers have the flexibility to adjust fuel usage if there were unforeseen and sudden increases in gas prices is perhaps something that lenders should take into account.

2.6 Conclusion

In this paper, I decomposed a short-run fuel use elasticity into changes in VMT and MPG. The changes in MPG came from changes in vehicle utilization behavior. I identified several of these types of behaviors and found that households are more likely to drive their most fuel efficient vehicle and switch or share vehicles in a way that increases fuel economy. In addition to safety and gasoline shocks, the presence of short-run changes are important in assessing policy aimed at decreasing fuel use, VMT, and pollution. Policy aimed at decreasing fuel use with mechanisms that increase prices will, in the short-run, result in proportionally smaller decreases in VMT and also probably more of an increase in MPG than expected.

Future work could explore how the presence of household switching behavior informs what we know about the preference for vehicle characteristics and the status quo bias. The willingness of an individual to switch vehicles indicates a tradeoff between utility of driving their preferred vehicle and switching to a different one. The presence of household switching also tells us about the benefits of energy efficient vehicles in the context of household ownership versus individual ownership. An energy efficient vehicle that is introduced into a household can possibly decrease fuel use more since it can be traded among several people. Perhaps policy makers should consider awarding tax credits for energy efficient vehicles with household fleet considerations in mind.

Chapter 2, in part, is currently being prepared for submission for publication of the material. Leung, William. The dissertation author was the primary investigator and author of this material.

Table 2.1: Summary Statistics

Variable	NHTS Survey Mean	Households with 2+ Vehicles Mean	S.D.	Min	Max
Persons per household	2.50	2.67	1.18	1	14
Vehicles per household	1.86	2.59	0.09	2	27
Drivers per household	1.88	2.11	0.62	0	9
Workers per household	1.34	1.18	0.90	0	6
Household income	10.24	12.82	4.98	1	18
Annual VMT	19,850	28,464	19,072	0	613,145
Percent urban	0.77	0.66			
Gas price	3.16	3.10	0.98	1.73	4.61
Weekend travel day	0.28	0.28			

Notes: Survey means from Summary of Travel Trends: 2009 NHTS and NHTS 2009 Household data files with sampling weights. Statistics for 2+ vehicle households are from 97,576 observations, including households with estimates of annual VMT for each household vehicle. Only one household with 2 vehicles had zero drivers. Annual VMT estimated from bestmile variable in NHTS data. Household income and percent urban are derived from categorical variable.
Population gas price and weekday travel day indicators are calculated as average gas price during the sample period. 2+ vehicle sample are weighted by number of households on each travel day.

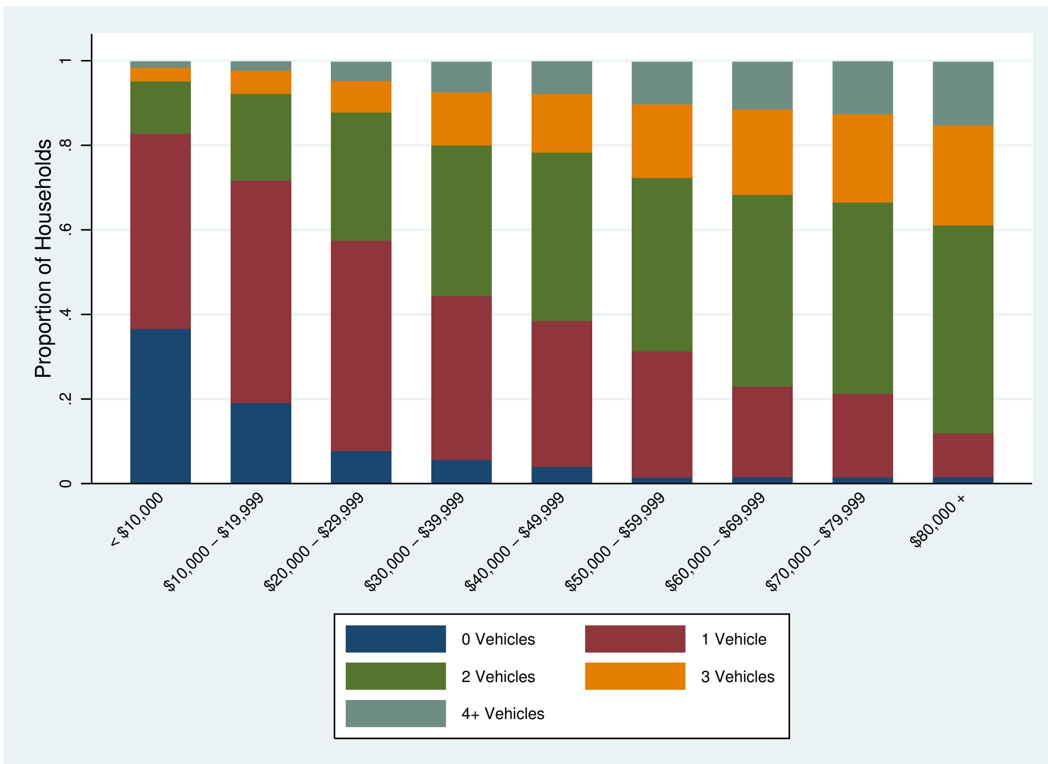

Figure 2.1: Vehicle ownership by household income

Table 2.2: Multiple vehicle ownership

Households that own		Proportion that also own:				
		Car	Van	SUV	Pickup	Motorcycle
Car	77,111	0.419	0.159	0.348	0.407	0.0691
Van	18,617		0.0750	0.239	0.352	0.0611
SUV	42,182			0.171	0.397	0.0795
Pickup	45,888				0.151	0.0993
Motorcycle	7,296					0.203

Table 2.3: OLS regression: Effect of gas price on travel day behavior

VARIABLES	(1) Fuel Use (gallons/day)	(2) VMT (miles/day)	(3) MPG (miles/gallon)
Gas Price	-0.0799***	-1.573***	0.158***
	(0.0260)	(0.577)	(0.0415)
Avg Daily Fuel Use	0.288***		
	(0.0118)		
Avg Daily VMT		0.313***	
		(0.00699)	
Avg Fleet MPG			0.818***
			(0.00589)
Feb-March	0.159***	3.840***	0.0334
	(0.0353)	(0.789)	(0.0590)
Apr-May	0.256***	5.765***	-0.0408
	(0.0527)	(1.164)	(0.0846)
Jun-Jul	0.343***	7.924***	0.0804
	(0.0764)	(1.698)	(0.121)
Aug-Sept	0.264***	6.178***	-0.00688
	(0.0616)	(1.371)	(0.0996)
Oct-Nov	0.173***	4.287***	0.0664
	(0.0404)	(0.917)	(0.0655)
Constant	1.320***	29.41***	4.208***
	(0.0686)	(1.442)	(0.173)
Observations	97,576	97,576	88,600
R-squared	0.058	0.054	0.450
DOW Fixed Effects	yes	yes	yes
Price Elasticity	-0.107	-0.0868	0.0188
% of Price Elasticity	1	0.815	0.175

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.4: Effect of fleet heterogeneity

	homogenous fleet			heterogenous fleet		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Fuel Use (gallons/day)	VMT (miles/day)	MPG (miles/gallon)	Fuel Use (gallons/day)	VMT (miles/day)	MPG (miles/gallon)
Gas Price	-0.0789**	-1.874**	0.0104	-0.0823**	-1.279	0.326***
	(0.0332)	(0.770)	(0.0195)	(0.0402)	(0.862)	(0.0806)
Avg Daily Fuel Use	0.331***			0.265***		
	(0.0107)			(0.0163)		
Avg Daily VMT		0.307***			0.306***	
		(0.0104)			(0.00945)	
Avg Fleet MPG			0.982***			0.730***
			(0.00185)			(0.00828)
Constant	1.129***	28.34***	0.405***	1.471***	31.80***	6.416***
	(0.0822)	(1.929)	(0.0654)	(0.105)	(2.154)	(0.284)
Observations	49,744	49,744	44,917	47,832	47,832	43,683
R-squared	0.056	0.044	0.849	0.057	0.057	0.316
Bi-Month Fixed Effects	yes	yes	yes	yes	yes	yes
DOW Fixed Effects	yes	yes	yes	yes	yes	yes
Price Elasticity	-0.113	-0.113	0.00131	-0.104	-0.0649	0.0366
% of Price Elasticity	1	0.997	0.0116	1	0.624	0.351

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

Notes: Homogenous households are defined as having a difference in MPG between their highest and lowest fuel economy vehicles of 7.5 MPG.

Table 2.5: Effect of income

	Income < twice poverty rate			Income > twice poverty rate		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Fuel Use (gallons/day)	VMT (miles/day)	MPG (miles/gallon)	Fuel Use (gallons/day)	VMT (miles/day)	MPG (miles/gallon)
Gas Price	-0.115**	-2.228**	0.216**	-0.0747**	-1.377**	0.147***
	(0.0493)	(1.107)	(0.0976)	(0.0308)	(0.688)	(0.0474)
Avg Daily Fuel Use	0.261***			0.287***		
	(0.0232)			(0.0140)		
Avg Daily VMT		0.282***			0.308***	
		(0.0154)			(0.00808)	
Avg Fleet MPG			0.758***			0.825***
			(0.0135)			(0.00669)
Constant	1.173***	26.06***	5.719***	1.395***	31.32***	3.996***
	(0.127)	(2.739)	(0.402)	(0.0822)	(1.726)	(0.197)
Observations	16,832	16,832	14,423	74,315	74,315	68,713
R-squared	0.054	0.058	0.408	0.057	0.050	0.454
Bi-Month Fixed Effects	yes	yes	yes	yes	yes	yes
DOW Fixed Effects	yes	yes	yes	yes	yes	yes
Price Elasticity	-0.195	-0.157	0.0262	-0.0943	-0.0712	0.0174
% of Price Elasticity	1	0.802	0.134	1	0.755	0.184

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

Notes: 2009 Poverty rate is the weighted average threshold defined for household size and annual income: 1, \$10,956; 2, \$13,991; 3, \$17,098; 4, \$21,954; 5, \$25,991; 6, \$29,405; 7, \$33,372; 8, \$37,252; 9+, \$44,366. Income in the NHTS data is a categorical variable. I label a household below twice the poverty rate if the range of its income category includes twice the poverty rate. Source: https://www.census.gov/hhes/www/poverty/data/threshld/thresh09.html

Table 2.6: Urban and rural households

	Urban			Rural		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Fuel Use (gallons/day)	VMT (miles/day)	MPG (miles/gallon)	Fuel Use (gallons/day)	VMT (miles/day)	MPG (miles/gallon)
Gas Price	-0.0633**	-1.156*	0.139***	-0.127***	-2.683***	0.191**
	(0.0315)	(0.702)	(0.0497)	(0.0460)	(1.015)	(0.0749)
Avg Daily Fuel Use	0.285***			0.274***		
	(0.0117)			(0.0203)		
Avg Daily VMT		0.300***			0.314***	
		(0.00821)			(0.0122)	
Avg Fleet MPG			0.848***			0.749***
			(0.00709)			(0.0106)
Constant	1.192***	27.63***	3.534***	1.688***	35.94***	5.686***
	(0.0802)	(1.748)	(0.209)	(0.123)	(2.552)	(0.309)
Observations	65,252	65,252	59,710	32,324	32,324	28,890
R-squared	0.044	0.045	0.479	0.073	0.064	0.381
Bi-Month Fixed Effects	yes	yes	yes	yes	yes	yes
DOW Fixed Effects	yes	yes	yes	yes	yes	yes
Price Elasticity	-0.0922	-0.0682	0.0162	-0.148	-0.131	0.0234
% of Price Elasticity	1	0.740	0.176	1	0.885	0.158

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

Notes: Decompositions by urban and rural designation defined by NHTS variable *URBRUR* for households owning two or more vehicles.

Table 2.7: Stops and average miles per stop

VARIABLES	(1) Stops On Travel Day	(2) Average Miles Per Stop
Gas Price	0.0106	-0.537**
	(0.0319)	(0.250)
Avg Daily VMT	0.0156***	0.0323***
	(0.000385)	(0.00257)
Constant	3.989***	11.318***
	(0.0800)	(0.612)
Observations	97,576	88,600
R-squared	0.073	0.004
Bi-Month Fixed Effects	yes	yes
DOW Fixed Effects	yes	yes

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

Table 2.8: Vehicle utilization

VARIABLES	(1) Used Max MPG	(2) Used Min MPG	(3) Used Max MPG Most	(4) Used Min MPG Most	(5) Efficient Fuel Use
Gas Price	0.0684***	-0.0531***	0.0437***	-0.0401***	0.0112***
	(0.00824)	(0.00793)	(0.00731)	(0.00753)	(0.00133)
Vehicle Count	-0.624***	-0.850***	-0.483***	-0.551***	0.000140
	(0.0117)	(0.0124)	(0.0115)	(0.0124)	(0.00171)
Household Size	-0.0396***	0.163***	-0.0523***	0.0486***	-0.0155***
	(0.00770)	(0.00773)	(0.00647)	(0.00656)	(0.00114)
ΔMPG	-0.0263***	-0.000433	-0.00881***	-0.00373***	-0.00398***
	(0.000870)	(0.000872)	(0.000844)	(0.000877)	(0.000145)
VMT_{minmpg}	0.00904***	0.00887***	0.00149**	0.00296***	-0.000205*
	(0.000734)	(0.000699)	(0.000615)	(0.000627)	(0.000113)
VMT_{maxmpg}	-0.000226	-0.000139	-0.000265	5.70e-05	-4.17e-05
	(0.000254)	(0.000248)	(0.000231)	(0.000237)	(4.08e-05)
Constant	1.006***	0.848***	0.879***	0.773***	0.566***
	(0.0471)	(0.0461)	(0.0426)	(0.0443)	(0.00734)
Observations	84,881	84,881	84,881	84,881	84,881
(Pseudo) R-squared	0.142	0.145	0.0382	0.0366	0.016
Trip purpose controls	yes	yes	no	no	no
DOW Fixed Effects	yes	yes	yes	yes	yes
Model	Logit	Logit	Logit	Logit	OLS

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Trip purpose controls are the number of trips originating from home by NHTS variable *WHYTRP1S*. Categories are work, school/religious, medical, shopping, social, family, transporting other, meals, and other.

Table 2.9: Switching behavior

VARIABLES	(1) Switched	(2) Switched to max MPG	(3) Switched to min MPG
Gas Price	0.0157	0.0553***	-0.0201
	(0.0127)	(0.0176)	(0.0201)
Vehicle Count	0.0163	-0.351***	-0.424***
	(0.0157)	(0.0287)	(0.0331)
Household Size	0.111***	0.0689***	0.123***
	(0.0111)	(0.0162)	(0.0175)
ΔMPG	0.00205	-0.00150	-0.00136
	(0.00137)	(0.00211)	(0.00241)
VMT_{minmpg}	-0.00314***	-0.00143	-0.00218
	(0.00110)	(0.00150)	(0.00167)
VMT_{maxmpg}	-0.000612	-0.00140**	-0.000453
	(0.000401)	(0.000625)	(0.000652)
Constant	-3.308***	-3.117***	-3.153***
	(0.0719)	(0.106)	(0.118)
Observations	78,013	78,013	78,013
Pseudo R-squared	0.0353	0.0308	0.0365
Trip purpose controls	yes	yes	yes
DOW Fixed Effects	yes	yes	yes
Model	logit	logit	logit

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Trip purpose controls are the number of trips originating from home by NHTS variable *WHYTRP1S*. Categories are work, school/religious, medical, shopping, social, family, transporting other, meals, and other.

Table 2.10: Sharing behavior

VARIABLES	(1) Any Shared Trips	(2) Shared Max MPG	(3) Shared Min MPG
Gas Price	-0.00706	0.0240**	-0.0354***
	(0.00822)	(0.0107)	(0.0114)
Vehicle Count	0.0596***	-0.338***	-0.387***
	(0.0107)	(0.0178)	(0.0189)
Household Size	0.0508***	-0.0468***	0.120***
	(0.00757)	(0.0104)	(0.0101)
ΔMPG	-0.00238***	-0.00769***	-0.00646***
	(0.000905)	(0.00130)	(0.00138)
VMT_{minmpg}	-0.00182***	-0.000591	1.02e-05
	(0.000707)	(0.000908)	(0.000943)
VMT_{maxmpg}	4.60e-05	-0.000350	0.000410
	(0.000254)	(0.000350)	(0.000349)
Constant	-1.196***	-0.957***	-1.408***
	(0.0457)	(0.0624)	(0.0655)
Observations	85,751	85,383	85,383
Pseudo R-squared	0.102	0.0750	0.0732
Trip purpose controls	yes	yes	yes
DOW Fixed Effects	yes	yes	yes
Model	logit	logit	logit

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Trip purpose controls are the number of trips originating from home by NHTS variable *WHYTRP1S*. Categories are work, school/religious, medical, shopping, social, family, transporting other, meals, and other.

Table 2.11: Differences in utilization by fleet heterogeneity

	Used High	Used Low	Used High Most	Used Low Most
Homogenous Fleets				
Average Proportion	0.761	0.719	0.437	0.407
Marginal Effect of Price	0.00730	-0.00826	0.00673	-0.00449
Heterogenous Fleets				
Average Proportion	0.651	0.534	0.360	0.272
Marginal Effect of Price	0.0222	-0.0157	0.0143	-0.0133

Table 2.12: Vehicle weight regressions

VARIABLES	(1) LbMT (1000lb-Miles)	(2) Avg Weight (Pounds)
Gas Price	-9.917***	-18.90***
	(2.842)	(5.126)
Annual LbMT/365	0.358***	
	(0.0110)	
Avg Fleet Weight		0.828***
		(0.00398)
Constant	131.8***	769.5***
	(6.963)	(28.35)
Observations	64,680	61,096
R-squared	0.058	0.527
Bi-Month Fixed Effects	Yes	Yes
DOW Fixed Effects	Yes	Yes
Price Elasticity	-0.142	-0.0158

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

Table 2.13: Elasticities by vehicle type

Vehicle Type	Price Coefficient	SE	Price Elasticity	Proportion of Vehicles	Avg. Weight
Car	0.202	(0.495)	0.0183	49.9%	3153
Van	-1.848**	(0.939)	-0.209	8.2%	4144
SUV	-1.877***	(0.675)	-0.187	19.4%	4214
Pickup	-1.796***	(0.577)	-0.265	17.8%	4355
Motorcycle	3.179***	(0.732)	1.890	3.3%	500

Notes: Table includes both single and multi-vehicle households. Results are similar when restricted to only multi-vehicle households. Results for vehicle types: RV and other trucks are not reported.

2.7 Chapter 2 Appendix

2.7.1 Distance to Work Regressions

This section has the regression results for decompositions by distance to work and decompositions by fleet heterogeneity for households living far from work. It also discusses the construction of the optimal travel day MPG mentioned in the discussion.

Constructing a measure of optimal fuel use

Unlike the *EFU* measure computed earlier, I try to take into account the possibility that households often need to take concurrent trips. For example if two household members worked on opposite sides of town, it would be difficult for all the VMT to be put into a single vehicle. In constructing this measure, I assume that VMT cannot be traded among vehicles so that the measure of optimal MPG for this two vehicle household would be the result of the highest MPG vehicle driving the longer leg to work and the lower MPG vehicles driving the shorter leg to work. I don't consider the household would allocating all driving to the highest MPG vehicle as a feasible option.

Specifically, optimal travel day MPG is equal to the average MPG if the largest VMT that any household vehicle took was assigned to the highest MPG vehicle, the second largest VMT that any household vehicle took was assigned to the lowest MPG vehicle, etc... I adjust this measure for households that own motorcycles since they are not always good substitutes for cars but are often the highest MPG vehicle. Thus for households that own a motorcycle, the optimal travel day MPG measure is equal to the minimum of actual travel day MPG or travel day MPG if the highest MPG car was assigned the largest VMT, the second highest MPG car was assigned the second largest VMT, etc... Results from the calculations in the discussion section are similar if this adjustment is not made.

Table 2.14: Distance to work

	Less than 10 Miles			10 to 20 Miles			More than 20 Miles		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Fuel Use	VMT	MPG	Fuel Use	VMT	MPG	Fuel Use	VMT	MPG
Price	-0.0458	-0.760	0.104	-0.138*	-2.991*	0.0711	-0.0449	-1.517	0.150
	(0.0494)	(1.109)	(0.0858)	(0.0730)	(1.686)	(0.110)	(0.0673)	(1.511)	(0.0910)
Avg Daily Fuel Use	0.226***			0.184***			0.315***		
	(0.0236)			(0.0230)			(0.0283)		
Avg Daily VMT		0.229***			0.172***			0.309***	
		(0.0133)			(0.0155)			(0.0159)	
Avg Fleet MPG			0.796***			0.801***			0.851***
			(0.0120)			(0.0161)			(0.0125)
Constant	1.483***	35.10***	4.702***	1.891***	46.74***	4.597***	2.328***	59.74***	3.346***
	(0.131)	(2.716)	(0.350)	(0.175)	(3.925)	(0.468)	(0.167)	(3.467)	(0.374)
Observations	21,270	21,270	20,076	10,556	10,556	10,223	18,794	18,794	18,188
R-squared	0.049	0.030	0.454	0.023	0.017	0.481	0.064	0.049	0.477
Month Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
DOW Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes

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

Table 2.15: Fleet heterogeneity and long commutes

	Homogenous Fleet			Heterogeneous Fleet		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Fuel Use	VMT	MPG	Fuel Use	VMT	MPG
Price	-0.00500	-1.352	-0.0551	-0.0836	-1.830	0.355**
	(0.0830)	(1.955)	(0.0420)	(0.102)	(2.247)	(0.163)
Avg Daily Fuel Use	0.361***			0.298***		
	(0.0227)			(0.0382)		
Avg Daily VMT		0.306***			0.298***	
		(0.0232)			(0.0214)	
Avg Fleet MPG			0.989***			0.769***
			(0.00368)			(0.0179)
Constant	2.042***	57.16***	0.377***	2.520***	63.82***	5.211***
	(0.210)	(5.115)	(0.135)	(0.239)	(4.749)	(0.587)
Observations	8,623	8,623	8,310	10,171	10,171	9,878
R-squared	0.057	0.039	0.882	0.069	0.050	0.341
Month Fixed Effects	yes	yes	yes	yes	yes	yes
DOW Fixed Effects	yes	yes	yes	yes	yes	yes

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

2.7.2 Asymmetric Price Responses

Consumers are thought to exhibit different responses to times when gas prices are rising versus when gas prices are falling. To examine this type of behavior, I run regressions separately for days when the price of gas was higher than one week prior and for when the price of gas was lower than one week prior. Table 2.16 reports the results from these regressions. Interestingly, it appears that the gasoline price elasticity of fuel use and VMT are driven by periods in which gas prices are increasing. Increasing and higher gas prices are associated with a statistically significant decrease in fuel use and VMT while the effect of high gas prices during time when gas price is decreasing does not have a statistically significant effect of fuel use and VMT. High prices are associated with statistically significant increases in MPG for both times of increasing and decreasing prices. This seems to suggest that while driving behavior responds quickly to gasoline price increases, changes in vehicle utilization are more permanent.

When looking at vehicle utilization, switching, and sharing, there are little differences between time periods of increasing prices and decreasing prices. This is in support of the similar findings for the MPG elasticity.

Table 2.16: Robustness: Asymmetric reactions to price

	Today's price higher than last week			Today's price Lower than last week		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Fuel Use	VMT	MPG	Fuel Use	VMT	MPG
Gas Price	-0.111***	-2.333***	0.122**	-0.0286	-0.237	0.225***
	(0.0361)	(0.787)	(0.0557)	(0.0377)	(0.858)	(0.0629)
Avg Daily Fuel Use	0.273***			0.298***		
	(0.0181)			(0.0155)		
Avg Daily VMT		0.293***			0.327***	
		(0.0111)			(0.00905)	
Avg Fleet MPG			0.811***			0.822***
			(0.00948)			(0.00751)
Constant	1.064***	23.27***	4.522***	0.863***	18.65***	4.134***
	(0.104)	(2.077)	(0.268)	(0.0948)	(1.946)	(0.230)
Observations	37,634	37,634	34,068	59,942	59,942	54,532
R-squared	0.053	0.051	0.445	0.061	0.056	0.452
Month Fixed Effects	yes	yes	yes	yes	yes	yes
DOW Fixed Effects	yes	yes	yes	yes	yes	yes
Price Elasticity	-0.138	-0.120	0.0133	-0.0403	-0.0136	0.0280
% of Price Elasticity	1	.870	.0963	1	0.337	0.695

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

2.7.3 Robustness Checks

Selection

One concern in estimating the price elasticity of travel day MPG is we are unable to observe MPG from households that chose not to drive. If unobservables in the decision to drive are multiples of errors in the households MPG, there is possible bias resulting for not controlling for selection.

I attempt to correct for possible selection problems with a Heckman Two-Step Estimator. I fit the model

$$MPG_{it} = \beta_0 P_t + M\hat{P}G_i + \gamma' S_t + \epsilon_{it} \tag{2.6}$$

where MPG_{it} is observed only if the household drove on the travel day. For the first stage, I estimate:

$$P(VMT_{it} > 0) = \Phi(\alpha_0 + \alpha_1 P_t + \alpha_2 M\hat{P}G_i + \delta' S_t + \theta' X_{it}) \tag{2.7}$$

X_{it} is a vector additional controls for the selection equation that I argue do not affect travel day MPG but do help predict whether or not any driving occurred on the travel day. Included X_{it} is the number of workers in the household, number of drivers in the household, the estimate of annual VMT of the household, whether or not the household has access to rail, the number of trips (driving or other) on the travel day, and the number of walking trips the household took last week.

Several of these characteristics are predetermined before the travel day and they should not have an effect on travel day MPG that is not already captured in the average fleet MPG for the household. The others (access to rail, number of walking trips last week) are household characteristics that indicate access to alternative modes of transportation and also likelihood of non-vehicle transportation. The number of travel day trips includes both driving and non-driving trips. I would suspect that vehicles facilitate taking more trips because they decrease travel time. Taking many trips in a day would help predict using a car, however it doesn't tell use what type of car would be used.

Table 2.17 shows results. The inverse mills ratio is 0.330 and significant at the 1% level. The additional regressors in the selection regression are all highly significant in predicting probability of driving on the travel day. However the gas price on the travel day does not appear to be a significant predictor of whether or not driving occurred on the travel day. As a result, even though there is selection present, this does not appear to bias the results on the effect of price on average travel day MPG. This remains true when run for the various specifications looking at heterogeneity in responses.

Table 2.17: Robustness: Heckman two-step for selection on the decision to drive

	Outcome	Selection	
	(1)	(2)	(3)
VARIABLES	MPG	Any Driving	mills
Gas Price	0.158***	-0.00663	
	(0.0414)	(0.0175)	
Avg Fleet MPG	0.819***	0.00331***	
	(0.00305)	(0.00128)	
Dec-Jan	-0.0705	-0.0476*	
	(0.0663)	(0.0276)	
Feb-March	-0.0315	0.0111	
	(0.0624)	(0.0265)	
Apr-May	-0.106*	0.00994	
	(0.0620)	(0.0266)	
Jun-Jul	0.0114	-0.00744	
	(0.0891)	(0.0376)	
Aug-Sept	-0.0756	-0.0320	
	(0.0705)	(0.0297)	
Worker Count		0.260***	
		(0.00977)	
Driver Count		-0.0591***	
		(0.0142)	
Annual VMT (bestmile)		-5.20e-07	
		(4.08e-07)	
Access to Rail		0.118***	
		(0.0190)	
# Trips		0.211***	
		(0.00219)	
Walk Trips Last Week		-0.00842***	
		(0.000516)	
λ			0.330***
			(0.107)
Constant	4.210***	-0.334***	
	(0.155)	(0.0785)	
Observations	97,576	97,576	97,576
DOW FE	yes	yes	yes
Price Elasticity	.0187	-	-

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

New Vehicles

Another concern in the identification of the MPG elasticity is whether or not this is just picking up changes due to purchases of new vehicles. Today's gas price is correlated with the gas price during the season. Perhaps the MPG elasticity that is being picked up is coming from households that bought new vehicles in expectation that the gas price would be high.

I run the same baseline regressions but exclude households with vehicles that were purchased within six months of the assigned travel day. Table 2.18 shows results. The estimates for price's affect on fuel use and VMT are very similar. The effect on MPG is slightly smaller. This suggests that newer vehicles contribute to a households ability to adjust to gas prices. This suggests that some of the travel day MPG elasticity may driven by the purchase and use of newer vehicles but doesn't necessarily indicate that household purchased vehicles these vehicles in response to current gas prices. Still, these results show that the majority of decreased fuel use from changes in MPG are present when excluding new vehicles.

Table 2.18: Robustness: Excluding newly purchased vehicles

	(1)	(2)	(3)
VARIABLES	Fuel Use	VMT	MPG
Gas Price	-0.0792***	-1.490**	0.130***
	(0.0285)	(0.637)	(0.0455)
Avg Daily Fuel Use	0.328***		
	(0.0168)		
Avg Daily VMT		0.371***	
		(0.00855)	
Avg Fleet MPG			0.830***
			(0.00680)
Constant	1.390***	30.66***	4.052***
	(0.0813)	(1.568)	(0.195)
Observations	74,986	74,986	67,901
R-squared	0.053	0.053	0.466
Bi-month Fixed Effects	yes	yes	yes
DOW Fixed Effects	yes	yes	yes
Price Elasticity	-0.110	-0.0853	0.0154
% of Price Elasticity	1	0.775	0.140

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

Alternative Specifications

I discuss several alternative model specifications below.

A common approach to estimating elasticities of demand is the log-log specification. I avoided this specification because some households didn't take trips in their cars on their travel day, resulting in zeros for fuel use and VMT. A log-log specification would drop these individuals from the estimation. This is problematic if gasoline prices induced households to not use their vehicles.

One alternative to the log-log model is a poisson regression with variance-covariance matrix estimated using theHuber-White Sandwich linearized estimator. I run a poisson regression of the form:

$$Y_{it} = e^{\beta_0 + \beta_1 \ln P_t + \hat{Y}_i + S_t} e^{\epsilon_{it}} \tag{2.8}$$

When run with log gas price, the coefficient β_1 can be interpreted as a price elasticity. Table 2.19 shows the results from this regression. The price elasticities of fuel use, VMT, and MPG are -0.0998, -0.0837, and 0.0169 respectively. The results are very similar to elasticity estimates from the OLS regressions.

I also run regressions that change the role of $\hat{Y}$. One alternative specification could be to use the ratio of travel day behavior and baseline behavior, $Y/\hat{Y}$ as the dependent variable. Table 2.20 shows the results of a regression of the from:

$$\frac{Y_{it}}{\hat{Y}_i} = \beta_0 + \beta_1 P_t + S_t + \epsilon_{it} \tag{2.9}$$

The table shows a similar pattern as the main specification. High gasoline price are associated with decreases in fuel use and VMT and increases in MPG. Consistent with the results from the main specification, the fuel use ratio exhibits a larger decrease than the VMT ratio. Since the dependent variable is a ratio, it is more difficult to transform these estimates back to an elasticity. This specification has much lower R^2 than the specification found in the paper. This is because there is no longer any household specific information used as explanatory variables.

Finally, I estimate the effect of prices using variables that are used in the construction of bestmile, instead of bestmile itself. For geographic characteristics, I include indicator variables for MSA size and census division. The included household characteristics are household size, household vehicle count, number or workers, and number of adults. I also include information on vehicle use by including a self reported estimate of annual miles traveled and the households average fleet fuel economy. Households often cannot remember or give a good estimate of annual miles traveled for each vehicle. Households that were unable to give an estimate for one of their vehicles were dropped from the sample. The construction of bestmile took this into consideration and adjusted accordingly. Compared to the regressions found in the paper, there are 25 additional regressors.

Table 2.21 shows the result from this regression. The estimated gasoline price elasticity is similar to the one estimated in the paper. The VMT elasticity is slightly larger in magnitude but also within the range of the one estimated in the paper. The baseline measure for MPG does not utilize the bestmile so a regression with average MPG as the dependent variable is not included in this table.

Price Variation

In my main specification I use a single price series for all states. In this section I use monthly state regular unleaded gasoline prices from the EIA and additional state tax information from the Federal Highway Association and the EIA.[18] Adding in price variation may also allow me to use more detailed seasonal fixed effects. Table 2.22 shows the results of the main specification for a variety of fixed effects and then results for a specification using state level price variation with imputed gasoline price data. The regressions with imputed prices also include state fixed effects because driving behavior and gasoline prices vary by state. The main results are similar for a variety of fixed effects from the level of season to week. This is true for both specifications with a single price series and imputed prices for each

[18] http://www.fhwa.dot.gov/policyinformation/statistics/2009/mf205.cfm and http://www.eia.gov/pub/oil_gas/petroleum/data_publications/petroleum_marketing_monthly/historical/2009/2009_12/pdf/enote.pdf.

Table 2.19: Poisson regression

VARIABLES	(1) Fuel Use	(2) VMT	(3) MPG
ln(Gas Price)	-0.0998***	-0.0837***	0.0169***
	(0.0329)	(0.0303)	(0.00468)
Daily Avg. Fuel	0.0319***		
	(0.00450)		
Daily Avg. VMT		0.00316***	
		(0.000245)	
Avg Fleet MPG			0.0281***
			(0.000176)
Constant	0.531***	3.548***	2.497***
	(0.0325)	(0.0342)	(0.00576)
Observations	97,576	97,576	88,600
Month Fixed Effects	yes	yes	yes
DOW Fixed Effects	yes	yes	yes
% of Price Elasticity	1	0.839	.169

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

state.

Once I add year-month fixed effects or year-week fixed effects, the results in the single price specification change. I suspect that this occurs because with fixed effects at this frequency, there is a high degree of multicollinearity. When using imputed price data, it appears as if the responses in terms of fuel use and VMT are larger as I increase the frequency of the fixed effects. The responses in MPG get slightly smaller, but the standard errors become increasingly large. This is an interesting pattern that should be investigated in future work.

Table 2.20: Dependent variable $Y/\hat{Y}$

VARIABLES	(1) Fuel Use	(2) VMT	(3) MPG
Gas Price	-0.106**	-0.0992*	0.00639***
	(0.0515)	(0.0517)	(0.00146)
Constant	1.125***	1.105***	0.989***
	(0.428)	(0.428)	(0.00344)
Observations	97,575	97,575	88,600
R-squared	0.000	0.000	0.002
Month Fixed Effects	yes	yes	yes
DOW Fixed Effects	yes	yes	yes

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

Table 2.21: Alternatives to bestmile

VARIABLES	(1) Fuel Use	(2) VMT
Gas Price	-0.0886***	-1.833***
	(0.0272)	(0.609)
Constant	2.068***	-0.0380
	(0.172)	(3.766)
Observations	88,600	88,600
R-squared	0.099	0.083
Month Fixed Effects	yes	yes
DOW Fixed Effects	yes	yes
Geographic Controls	yes	yes
Household Characteristics	yes	yes
Vehicle Use Controls	yes	yes
Price Elasticity	-0.108	-0.0918

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

Table 2.22: Different fixed effects

Single Price Series			
	(1)	(2)	(3)
	Fuel Use	VMT	MPG
None	0.0156	0.599**	0.164***
	(0.0106)	(0.240)	(0.0169)
Season	-0.0571***	-1.244***	0.153***
	(0.0191)	(0.426)	(0.0302)
Bi-Month	-0.0799***	-1.573***	0.158***
	(0.0260)	(0.577)	(0.0415)
Month	-0.127***	-2.423**	0.178***
	(0.0407)	(0.955)	(0.0650)
Week	-0.161***	-2.822**	0.211***
	(0.0493)	(1.133)	(0.0800)
Year-Month	-0.0908	-2.713	0.0936
	(0.0823)	(1.972)	(0.133)
Year-Week	-0.194	-1.815	0.0355
	(0.358)	(9.260)	(0.579)

Imputed Prices For States			
	(1)	(2)	(3)
	Fuel Use	VMT	MPG
None	0.00872	0.429*	0.165***
	(0.0115)	(0.258)	(0.0184)
Season	-0.0688***	-1.547***	0.147***
	(0.0196)	(0.435)	(0.0311)
Bi-Month	-0.0962***	-2.029***	0.157***
	(0.0271)	(0.599)	(0.0431)
Month	-0.139***	-2.887***	0.161**
	(0.0407)	(0.954)	(0.0651)
Week	-0.189***	-3.746***	0.159**
	(0.0489)	(1.120)	(0.0799)
Year-Month	-0.153**	-4.087**	0.0722
	(0.0680)	(1.597)	(0.112)
Year-Week	-0.363***	-8.598***	-0.120
	(0.116)	(2.600)	(0.205)

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

Chapter 3

Biofuel and the Regulation of Life Cycle Emissions

3.1 Introduction

While market based mechanisms have often been regarded as optimal for regulating environmental externalities, several notable environmental regulations are instead using intensity standards based off of life cycle emissions as the mechanism to regulate emissions. Rather than regulating externalities at each independent upstream source, a single rule can be applied downstream that limits emissions for the entire life cycle of a process. For example: California's Low Carbon Fuel Standard[1], EU's Fuel Quality Directive, British Columbia's Renewable and Low Carbon Fuel Requirements Regulation each have life cycle analysis components. There have also been recent developments pushing low carbon fuel standards in Oregon and Washington.

Life cycle analysis (LCA) assess the environmental impacts of a production process, taking into account all activity from production, use, and disposal. In the context of the economics of regulation, the output of an LCA is a single value that indicates how resource intensive or polluting a partial production process is. An LCA based intensity standard requires the output of the LCA to be below a specific value. In the cases we consider below, we assume that the LCA aggregates a single externality (for example, all carbon emissions involved in the production and use of a particular renewable fuel) but our results can also be applied to weighted combinations of pollutants according to health or other impacts.

In this paper we study LCA based intensity standards. A life cycle based intensity standard placed on a product has potential to transmit incentives for more efficient production upstream. We find that a life cycle analysis based intensity standard on emissions can achieve productive efficiency, pushing incentives for cleaner production upstream, and achieve first best with an additional tax on the final good. This result is also found in Holland (2012). We extend the analysis by looking at the role of overlapping regulation. Additional command and control regulation on upstream and downstream emissions do not necessarily distort efficiency in production.

[1]See Holland et al. (2009); Lade and Lin (2013) as examples studying the economic impacts of California's LCFS

However, additional upstream or downstream taxes on emissions are inefficient. Finally, we provide some empirical evidence that firms subject to life cycle analysis based intensity standards lower the carbon intensity of their fuels over time.

3.2 Model

We study how LCA based intensity standards transmit economic incentives throughout the production process and show that an LCA based intensity standard can achieve the efficient input ratio.

Consider a firm that produces a final good Z. The firm can use a clean input (L) and a dirty input (X). These can be used to create an intermediate good, $Y = G_Y(L_Y, X_Y)$. Both inputs and the intermediate good can be used to produce a final good $Z = G_Z(L_Z, X_Z, Y)$. A vertically integrated producer of Z faces a cost function $C(L_Y, L_Z, X_Y, X_Z) = w(L_Y + L_Z) + p_X(X_Y + X_Z)$ and the production function can be represented as $Z = F(L_Y, L_Z, X_Y, X_Z)$. We assume $F(\cdot)$ is increasing in inputs and is concave.[2] In the absence of regulation, the cost minimization problem to produce $\bar{Z}$ of the final good is:

$$\min_{L_Y, L_Z, X_Y, X_Z} w(L_Y + L_Z) + p_X(X_Y + X_Z) + \lambda_1(\bar{Z} - F(\cdot))$$

where the solution is characterized by the following equations:

$$w = \lambda_1 \left(\frac{\partial F}{\partial L_i}\right); \qquad p_X = \lambda_1 \left(\frac{\partial F}{\partial X_i}\right)$$

for $i = Y, X$. This is the standard solution that equates the input costs to the marginal rate of technical substitution.

If there are external costs associated with the use of the dirty good that are not priced, then too much X will be used in the production of the final good. Efficient input ratios for the production of Z can be attained with a tax on X equal

[2]The appendix illustrates several of these results for the case of Cobb-Douglas production functions.

to its marginal damage and would be characterized by:

$$w = \lambda_1 \left(\frac{\partial F}{\partial L_i} \right); \qquad p_X + t = \lambda_1 \left(\frac{\partial F}{\partial X_i} \right)$$

for $i = Y, X$.

An LCA based intensity standard places a limit on the dirtiness of one unit of the final good. In our context:

$$\frac{X_Y + X_Z}{\bar{Z}} \leq \sigma \tag{3.1}$$

The cost minimization problem faced by the producer that is subject to an LCA based intensity standard is then:

$$\begin{aligned} \min_{L_Y, L_Z, X_Y, X_Z} & w(L_Y + L_Z) + p_X(X_Y + X_Z) \\ & + \lambda_1(\bar{Z} - F(\cdot)) + \lambda_2 \left(X_Y + X_Z - \sigma \bar{Z} \right) \end{aligned}$$

and if the standard binds, then the solution is characterized by:

$$\begin{aligned} w &= \lambda_1 \left(\frac{\partial F}{\partial L_i} \right) \\ p_X + \lambda_2 &= \lambda_1 \left(\frac{\partial F}{\partial X_i} \right) \end{aligned} \tag{3.2}$$

for $i = X, Z$. If the standard is set such that $\lambda_2^* = t$, then the first order conditions under the LCA based intensity standard are identical to those under a tax and the LCA based standard archives the efficient input ratio. Holland (2012) shows that an additional tax on Z can achieve first best consumption.

The efficient input mix can also be achieved under and LCA based intensity standard with credits that can be purchased. The producer of the fuel would instead face the minimization problem:

$$L = \min_{L_Y, L_Z, X_Y, X_Z} w(L_Y + L_Z) + p_X(X_Y + X_Z) + p_R R$$
$$+ \lambda_1(\bar{Z} - F(\cdot)) + \lambda_2 \left(X_Y + X_Z - R - \sigma \bar{Z}\right)$$

where p_R is the price of a credit and R is the number of credits purchased. The solution to the minimization problem satisfies these first order conditions:

$$w = \lambda_1 \left(\frac{\partial F}{\partial L_i}\right)$$
$$(p_X + \lambda_2) = \lambda_1 \left(\frac{\partial F}{\partial X_i}\right)$$
$$p_R = \lambda_2$$

for $i = Y, Z$. If the credit price is equal to marginal damages, the producer will have the efficient output ratio.

3.2.1 Overlapping Regulation

The production life cycle for any product often spans state and international borders where upstream and downstream processes may be subject to different regulations. In this section we explore how various types of overlapping regulation interact with life cycle based intensity standards.

Command and Control

We show that both command and control regulation of the form, "total pollution must not exceed $\tilde{X}$," and upstream intensity standards are compatible with LCA based intensity standards. A firm facing a life cycle based intensity standard and command and control regulation faces the problem:

$$\min_{L_Y, L_Z, X_Y, X_Z} w(L_Y + L_Z) + p_X(X_Y + X_Z)$$
$$+ \lambda_1(\bar{Z} - F(\cdot)) + \lambda_2 \left(X_Y + X_Z - \sigma\bar{Z}\right) + \lambda_3(X_Y + X_Z - \tilde{X})$$

where the solution is characterized by:

$$w = \lambda_1 \left(\frac{\partial F}{\partial L_i}\right)$$
$$p_X + \lambda_2 + \lambda_3 = \lambda_1 \left(\frac{\partial F}{\partial X_i}\right)$$
$$\lambda_2 \left(X_Y + X_Z - \sigma\bar{Z}\right) = 0; \qquad \lambda_2 \geq 0; \qquad \frac{X_Y + X_Z}{\bar{Z}} - \sigma \leq 0$$
$$\lambda_3(X_Y + X_Z - \tilde{X}) = 0; \qquad \lambda_3 \geq 0; \qquad X_Y + X_Z - \tilde{X} \leq 0$$

For a properly chosen intensity standard, any non-binding command and control regulation will not change the chosen input ratio. $\lambda_3 = 0$ and production will be efficient in inputs.

Similarly, an LCA based intensity standard combined with an upstream intensity standard can achieve the efficient input mix if the upstream standard is not binding. An upstream intensity standard taking form $X_Y/Y \leq \omega$ in combination with our LCA based intensity standard would result in the following cost minimization problem for our producer.

$$\min_{L_Y, L_Z, X_Y, X_Z} w(L_Y + L_Z) + p_X(X_Y + X_Z)$$
$$+ \lambda_1(\bar{Z} - F(\cdot)) + \lambda_2 \left(X_Y + X_Z - \sigma\bar{Z}\right) + \lambda_3 \left(X_Y - \omega G_Y(\cdot)\right)$$

with first order conditions:

$$
\begin{aligned}
w + \lambda_3 \left(-\omega \frac{\partial G_Y}{\partial L_Y} \right) &= \lambda_1 \left(\frac{\partial F}{\partial L_Y} \right) \\
w &= \lambda_1 \left(\frac{\partial F}{\partial L_Z} \right) \\
p_X + \lambda_2 + \lambda_3 \left(1 - \omega \frac{\partial G_Y}{\partial X_Y} \right) &= \lambda_1 \left(\frac{\partial F}{\partial X_Y} \right) \\
p_X + \lambda_2 &= \lambda_1 \left(\frac{\partial F}{\partial X_Z} \right)
\end{aligned}
$$

If the upstream intensity standard is not binding, so that $\lambda_3 = 0$, it will again be possible for the first order conditions to be identical to those found under a tax. The same exercise can be done to show that a downstream intensity standard in combination with a life cycle based intensity standard can still result in the efficient input allocation.

Taxes On X

While additional command and control regulation or additional upstream or downstream intensity standards do not affect efficiency in production, price based regulations in combination with life cycle based intensity standards will not always allow for efficiency in production. A producer facing both an LCA based intensity standard and a tax, τ, on the dirty good would face the following minimization problem:

$$
\begin{aligned}
\min_{L_Y, L_Z, X_Y, X_Z} \; & w(L_Y + L_Z) + (p_X + \tau)(X_Y + X_Z) \\
& + \lambda_1(\bar{Z} - F(\cdot)) + \lambda_2 \left(X_Y + X_Z - \sigma \bar{Z} \right)
\end{aligned}
$$

If the LCA based intensity standard is binding, the producer faces the following first order conditions:

$$w = \lambda_1 \left(\frac{\partial F}{\partial L_i} \right)$$
$$(p_X + \tau + \lambda_2) = \lambda_1 \left(\frac{\partial F}{\partial X_i} \right)$$

Proposition 1. *Let σ be the LCA based intensity standard that achieves efficient production. Under an LCA based intensity standard, σ, and a tax, τ, we have $\partial\lambda_2/\partial\tau = -1$, for $\tau < t$ where t is the first best tax.*

Proof. Rearranging the first order conditions gives:

$$\lambda_2 = \frac{\partial F/\partial X_i}{\partial F/\partial L_i} w - p_X - \tau \tag{3.3}$$

Taking the derivative with respect to τ gives:

$$\frac{\partial \lambda_2}{\partial \tau} = \frac{\left(\frac{\partial^2 F}{\partial X_i^2} \frac{\partial X_i}{\partial \tau} \right) \frac{\partial F}{\partial L_i} - \left(\frac{\partial^2 F}{\partial L_i^2} \frac{\partial L_i}{\partial \tau} \right) \frac{\partial F}{\partial X_i}}{\left(\frac{\partial F}{\partial L_i} \right)^2} w - 1 \tag{3.4}$$

We will show $\partial X_i/\partial\tau = \partial L_i/\partial\tau = 0$ for $\tau < t$.

Cost minimizing behavior implies that $\partial L_i/\partial\tau \geq 0$ since an increase in the tax makes the use of X more expensive and similarly $\partial X_i/\partial\tau \leq 0$. Assume that $\partial L_Y/\partial\tau > 0$. Then the first order conditions require $\partial L_Z/\partial\tau > 0$ as well so that $\partial F/\partial L_Y = \partial F/\partial L_Z$. Cost minimization would require no additional production above $\bar{Z}$ so this would mean that both $\partial X_i/\partial\tau < 0$ for $i = Y, Z$. At this new solution we would have $X_Y + X_Z < \sigma\bar{Z}$ and so the Kuhn-Tucker conditions would require $\lambda_2 = 0$.

We now show that with the LCA based standard that achieves efficient production by itself and an overlapping tax, (σ, τ), that $\lambda_2 = 0$ if and only if $\tau > t$ (which would be a contradiction). First, say we have (σ, τ) where $\tau > t$. Denote

$X_i(\infty, \tau)$ and $L_i(\infty, \tau)$ as the inputs used with no standard and only a tax.[3]. We know that $X_i(\sigma, 0) = X_i(\infty, t) > X_i(\infty, \tau)$. Thus, a standard added to a tax, $\tau > t$ is non-binding and so $\lambda_2 = 0$.

Next we show that with a standard combined with a tax, τ, if $\lambda_2 = 0$ then $\tau > t$. Assume that instead $\tau \leq t$. We then have $X_i(\infty, \tau) \geq X_i(\infty, t) = X_i(\sigma, 0)$. Case 1: if $\tau = t$, then σ is binding. Any decrease in σ would require a decrease in total quantity of X used and so $\lambda_2 > 0$, a contradiction. Case 2: if $\tau < t$ then $X_i(\infty, \tau) > X_i(\infty, t) = X_i(\sigma, 0)$. Let

$$V_1 = \min_{L_Y, L_Z, X_Y, X_Z} w(L_Y + L_Z) + (p_X + \tau)(X_Y + X_Z) + \lambda_1(\bar{Z} - F(\cdot)) \tag{3.5}$$

$$\begin{aligned} V_2 = \min_{L_Y, L_Z, X_Y, X_Z} & w(L_Y + L_Z) + (p_X + \tau)(X_Y + X_Z) \\ & + \lambda_1(\bar{Z} - F(\cdot)) + \lambda_2(X_Y + X_Z - \sigma\bar{Z}) \end{aligned} \tag{3.6}$$

We have $V_1 < V_2$ since $X_i(\infty, \tau) \neq X_i(\sigma, 0)$. Thus, $\lambda_2 > 0$ which is again a contradiction. It must be instead that $\tau > t$.

So our first assumption that $\partial L_i / \partial \tau > 0$ implies $\tau > t$ which is a contradiction. Thus $\partial L_i / \partial \tau = \partial X_i / \partial \tau = 0$. $\square$

Proposition 1 implies that the combination of the proper LCA based intensity standard and a tax on the dirty good can still achieve the efficient production mix. Increases in the tax directly trade off with the shadow price of the LCA constraint.

Unlike the case of command and control regulation, we cannot achieve the efficient input ratio in production if there is a tax placed only on the upstream production process or only on the downstream production process. For example in the case of a tax on upstream use of the dirty good, τ_U the producer faces:

$$\begin{aligned} \min_{L_Y, L_Z, X_Y, X_Z} & w(L_Y + L_Z) + (p_X + \tau_U)X_Y + p_X X_Z \\ & + \lambda_1(\bar{Z} - F(\cdot)) + \lambda_2\left(X_Y + X_Z - \sigma\bar{Z}\right) \end{aligned}$$

[3] $\sigma = \infty$ would mean the producer can use as much X as desired on production

and the solution is characterized by:

$$
\begin{aligned}
w &= \lambda_1 \left(\frac{\partial F}{\partial L_i} \right) \\
(p_X + \tau_U + \lambda_2) &= \lambda_1 \left(\frac{\partial F}{\partial X_Y} \right) \\
(p_X + \lambda_2) &= \lambda_1 \left(\frac{\partial F}{\partial X_Z} \right)
\end{aligned}
$$

for $i = Y, Z$. Here we cannot equate marginal productivity and social marginal cost among both of our dirty inputs. If the tax and standard place the correct price for upstream use of X, the shadow price on the downstream use of X will be too low. Similarly, if the intensity standard results in the correct shadow costs for the downstream good, its combination with the tax will make upstream use of X too expensive. $\partial\lambda_2/\partial\tau$ is also ambiguous in this case.

$$
\frac{\partial \lambda}{\partial \tau} = -1 + \lambda_1 \frac{\partial^2 F}{\partial X_Y^2} \frac{\partial X_Y}{\partial \tau} + \frac{\partial F/\partial X_Y}{\partial F/\partial L_i} \left(-\lambda_1 \frac{\partial^2 F}{\partial L_i^2} \frac{\partial L_i}{\partial \tau} \right) \tag{3.7}
$$

The second and third terms of this expression are non-negative. This implies that increases in the tax are met with a a smaller decrease in the change in the shadow value of the LCA intensity standard constraint, and in fact it is possible for $\partial\lambda_2/\partial\tau > 0$.

Should regulators considering LCA based intensity standards be worrying about upstream regulation in other part of the country? These results suggest that things like upstream cap-and-trade in the electricity market or upstream regulation on farming in the midwest or abroad are relevant to downstream policy on fuels.

3.3 Evidence

Our model suggests that producers subject to life cycle based intensity standards are incentivized to find efficient methods to reduce emissions both in upstream and downstream production processes. In this section, we explore whether this type of behavior appears to be occurring in the California Low Carbon Fuel Standard.

Under California's LCFS, fuel producers must ensure that the average carbon intensity, measured in grams of carbon-dioxide-equivalent per megajoule of fuel energy (gCO2e/MJ), of fuels sold in California must be below a specific decreasing standard. Fuels that are cleaner than the standard generate credits that can be banked or traded, and fuels that are dirtier than the standard generate deficits that must be settled thorough purchases of clean fuels or credits. The LCFS requires fuel producers to determine the carbon intensity of their own fuels and the California Air Resources Board has developed Board approved carbon intensity values on a lookup table to facilitate the implementation of the LCFS. However, if a fuel producer has a production process that is cleaner than the Board approved carbon intensity or is not represented by current approved pathways, they can apply for a new fuel pathway to be added to the lookup table by performing their own LCA.[4]

Making adjustments to the production processes of fuel pathways so that they achieve lower carbon intensities than those found in the ARB approved pathways, and the creation of completely new fuel pathways could be evidence that the incentives present in an intensity standard are working. Since December 2010, at least 103 applications for improvements on fuel pathways have been approved and at least 31 applications for completely new pathways have been approved. Many of these applications credit improvements in carbon intensity to innovations in plant efficiency or to a cleaner mix of power in fuel production. For example, Illinois River Energy submitted an application for a corn ethanol pathway that achieved a lower carbon intensity than the Air Resources Board approved pathway. The summary states:

> Both IRE pathways achieve lower carbon intensity values relative to the reference pathways through two principle means. First, the plant incorporates a modern plant design developed by ICM that results in less energy use... Second, electricity use at the IRE plant is below the 1.08 kW-hr per gallon that is assumed for the reference pathway. *Staff Summary, Method 2A Application, Illinois River Energy* (2012)

Many other applications for fuel pathways also credit efficient plant design from

[4]Cal (2010)

ICM as a significant reason for why carbon intensity is lower than the Air Resources Board baseline.

We document changes in the carbon intensity. The data we use provides carbon intensities of approved and pending fuels, as well as information about registered biofuel facilities under the LCFS. The data provides a snapshot of the state of the CA LCFS in three separate time periods: March 2014, May/June 2014, and May 2015. Tables 3.1 and 3.2 provide summary statistics of carbon intensity by fuel type for the pending and approved pathways respectively. Table 3.1 shows that there have been slight improvements in the carbon intensity of all pending fuels regulated under the LCFS over time. The average carbon intensity of pending biodiesel, corn based ethanol, and sugarcane based ethanols is lower in spring 2015 than in spring 2014. There have also been some changes in number of these approved pathways. Table 3.2 suggests that there have been decreases in carbon intensity of some approved fuels types. The average carbon intensity of approved fuels is lower in 2015 for corn based ethanol, sorghum based ethanol, and sugarcane. However, the average carbon intensity of approved biodiesel and rendered tallow based fuels is higher in 2015 than in 2014. Despite being higher than the previous year, the average carbon intensity for these fuels are still well below the carbon intensity required for 2015 compliance, 96.48 gCO2e/MJ. Thus these new biofuels will still be generating credits.

The list of pending and approved fuels changes over time. Some fuels that were pending in 2014 are still pending in 2015, others become approved by 2015, and others are modified to have different carbon intensity values. Similarly, the list of approved fuels change over time as some pathways are replaced by more fuel efficient processes and as the list grows to accommodate recently approved pathways. Tables 3.3 and 3.4 provide summary statistics for each time period, documenting the average carbon intensities for pending and approved pathways for fuels new to those time periods. Table 3.3 indicates that new pending pathways are generally cleaner than their predecessors. For biodiesel, pathways introduced in spring 2015 are about 25% cleaner than pending pathways in spring 2014, and we also observe cleaner pathways in corn and sugarcane based ethanol. When considering new approved pathways, we don't see the same trend in table 3.4. While all fuels that are approved in 2015 still generate credits under the LCFS, the average carbon intensity of newly approved fuels in 2015 are higher than those than were already approved in spring 2014.

To get a better sense of sense of the trends in carbon intensity over time, we consider changes in carbon intensity of pending and approved pathways within the same company or same production facility. Companies will have different production technologies, so controlling for company characteristics may allow us to observe changes in carbon intensity that come from improvements in technology or changes in the production processes. Life cycle analysis takes into account energy that is used in the transportation of fuel to California. Thus, the location of the biofuel facility may be an important factor in total carbon intensity. We run a simple regression of the form:

$$\text{Carbon Intenisty}_{cfi} = \text{Month of Sample}_{cfi} + \Theta X + \epsilon_{cfi} \tag{3.8}$$

where c, f, and i index the company, facility, and fuel pathway respectively and an observation records a fuel pathway only in the month that we first observe it in the data. The vector X includes fixed effects and in our specification will include the company $\times$ fuel type interactions, facility $\times$ fuel type interactions, and facility $\times$ company $\times$ fuel type interactions.

Tables 3.5 and 3.6 show the results and provide suggestive evidence that when looking within a company, carbon intensity appears to be decreasing over time. Table 3.5 shows the results of this regression for approved pathways. The results are not statistically significant, but the sign of each coefficient on the month of sample indicates that approved pathways appear to be getting cleaner over time and we should expect on average, somewhere between a 0.09 to 0.46 gCO2e/MJ decrease in carbon intensity each month. Similarly, table 3.6 shows the results of the regression for pending pathways. Column 1 shows the results with company $\times$ fuel type fixed effects, and suggests that we should see about a 2.07 gCO2e/MJ decrease in the average carbon intensity of newly pending pathways each month. Columns 2 and 3 show the results with facility $\times$ fuel type fixed effects and company $\times$ facility $\times$ fuel type fixed effects. While the magnitude of the coefficient suggests a similar effect, it is not statistically significant.

While the empirical analysis only provides suggestive evidence that the LCFS results in lower carbon intensity over time, we can find evidence of fuel producers making changes to their production processes in specific case studies. For example, in 2010, White Energy applied for twelve improved pathways under the LCFS which improved on the the ARB's default fuel pathways. In 2014, White Energy applied for three pathways to replace four of the pathways in its previous application. The ARB staff summary of the application notes that:

> The only difference between the two sorghum-based pathways is the source of the sorghum used: Sorghum from fields requiring soil pH regulation through lime applications enters the ethanol production process with a CI reflecting the GHG emissions associated with the production and use of that lime. Sorghum from fields not requiring lime applications enters the ethanol production process without a CI increment reflecting lime use. *Staff Summary, Method 2A Application, White Energy: Plainview Bioenergy, LLC* (2014)

White Energy was able to find a method to decrease the carbon intensity of its fuels through changing a single downstream input. We suspect that as the LCFS develops, more behavior such as this will occur and be documented.

3.4 Conclusion

This paper developed a model where emissions are regulated using a life cycle analysis based intensity standard and found that this type of regulation is able to achieve the efficient ratio of inputs in production. We highlighted how LCA based intensity standards interact with other standards and with different taxes. The main finding was that efficiency in production could still be achieved with overlapping command and control regulation and up or downstream intensity standards, while an upstream tax on carbon would not be ale to achieve efficiency in production. We found some evidence that within companies, the carbon intensity of newly pending fuels is lower over time. Finally, we provided anecdotal evidence that firms do respond to incentives that are present under LCA based regulation.

Chapter 3 is joint work with Mark Jacobsen and Benjamin Miller.

Table 3.1: Carbon intensity of pending pathways over time

Fuel Type		Month of Sample		
		Sp. 2014	Sum. 2014	Sp. 2015
Biodiesel	Mean	41.30	41.68	39.06
	Std. Dev.	30.54	30.34	29.35
	Min.	4	4	4
	Max.	83.25	83.25	83.25
	Count	52	58	60
Corn Based Ethanol	Mean	96.43	96.43	96.31
	Std. Dev.	7.260	7.260	7.144
	Min.	90.1	90.1	90.1
	Max.	120.99	120.99	120.99
	Count	36	36	38
Sorghum Based Ethanol	Mean	91.03	91.03	91.03
	Std. Dev.	6.022	6.022	6.022
	Min.	85.81	85.81	85.81
	Max.	96.24	96.24	96.24
	Count	4	4	4
Molasses Based Ethanol	Mean	29.19	29.19	29.19
	Std. Dev.			
	Min.	29.19	29.19	29.19
	Max.	29.19	29.19	29.19
	Count	1	1	1
Sugarcane Ethanol	Mean	70.63	70.61	70.58
	Std. Dev.	5.38	5.41	5.43
	Min.	58.4	58.4	58.4
	Max.	84.71	84.71	84.71
	Count	105	104	103

Table 3.2: Carbon intensity of approved pathways over time

Fuel Type		Month of Sample		
		Sp. 2014	Sum. 2014	Sp. 2015
Biodiesel	Mean	33.38	33.82	35.60
	Std. Dev.	29.15	29.40	29.32
	Min.	4	4	4
	Max.	83.25	83.25	88.59
	Count	64	72	90
Biomethane	Mean	-15.29	-15.29	-15.29
	Std. Dev.			
	Min.	-15.29	-15.29	-15.29
	Max.	-15.29	-15.29	-15.29
	Count	1	1	1
Corn Based Ethanol	Mean	90.22	90.06	89.98
	Std. Dev.	6.72	7.01	7.01
	Min.	76.75	63.88	63.88
	Max.	120.99	120.99	120.99
	Count	165	166	168
Sorghum Based Ethanol	Mean	83.21	82.93	82.48
	Std. Dev.	11.91	11.99	12.10
	Min.	56.56	56.56	56.56
	Max.	99.89	99.89	99.89
	Count	55	56	55
Molasses Based Ethanol	Mean	21.11	21.11	21.11
	Std. Dev.	0.91	0.91	0.91
	Min.	21.47	21.47	21.47
	Max.	22.75	22.75	22.75
	Count	2	2	2
Sugarcane Based Ethanol	Mean	67.37	67.17	66.83
	Std. Dev.	5.67	5.70	5.73
	Min.	58.4	58.4	58.4
	Max.	79.11	79.11	79.11
	Count	50	52	56
Waste Based Ethanol	Mean	71.4	71.4	71.4
	Std. Dev.			
	Min.	71.4	71.4	71.4
	Max.	71.4	71.4	71.4
	Count	1	1	1
Rendered Tallow to Diesel	Mean	26.56	26.56	31.01
	Std. Dev.	9.77	9.77	12.12
	Min.	19.65	19.65	16.21
	Max.	33.46	33.46	49.69
	Count	2	2	6

Table 3.3: Carbon intensity of new pending pathways

Fuel Type		Month of Sample		
		Sp. 2014	Sum. 2014	Sp. 2015
	Mean	41.30	34.96	30.41
	Std. Dev.	30.54	28.74	24.87
Biodiesel	Min.	4	4	4
	Max.	83.25	83.25	83.25
	Count	52	9	12
	Mean	96.43		94.25
	Std. Dev.	7.260		8.87
Corn Based Ethanol	Min.	90.1		90.1
	Max.	120.99		98.4
	Count	36		2
	Mean	91.03		
	Std. Dev.	6.022		
Sorghum Based Ethanol	Min.	85.81		
	Max.	96.24		
	Count	4		
	Mean	29.19		
	Std. Dev.			
Molasses Based Ethanol	Min.	29.19		
	Max.	29.19		
	Count	1	1	1
	Mean	70.63	62.4	62.4
	Std. Dev.	5.38	5.66	5.66
Sugarcane Ethanol	Min.	58.4	58.4	58.4
	Max.	84.71	66.4	66.4
	Count	105	2	4

Table 3.4: Carbon intensity of new approved pathways

Fuel Type		Month of Sample		
		Sp. 2014	Sum. 2014	Sp. 2015
Biodiesel	Mean	33.38	34.79	40.73
	Std. Dev.	29.15	32.08	28.04
	Min.	4	4	4
	Max.	83.25	83.25	88.59
	Count	64	9	20
Biomethane	Mean	-15.29		
	Std. Dev.			
	Min.	-15.29		
	Max.	-15.29		
	Count	1		
Corn Based Ethanol	Mean	90.22	63.88	91.73
	Std. Dev.	6.72		6.91
	Min.	76.75	63.88	81.4
	Max.	120.99	63.88	98.4
	Count	165	1	7
Sorghum Based Ethanol	Mean	83.21	67.5	84.37
	Std. Dev.	11.91		10.29
	Min.	56.56		77.83
	Max.	99.89		96.24
	Count	55		3
Molasses Based Ethanol	Mean	21.11		
	Std. Dev.	0.91		
	Min.	21.47		
	Max.	22.75		
	Count	2		
Sugarcane Based Ethanol	Mean	67.37	62.4	62.4
	Std. Dev.	5.67	5.66	4.62
	Min.	58.4	58.4	58.4
	Max.	79.11	66.4	66.4
	Count	50	2	4
Waste Based Ethanol	Mean	71.4		
	Std. Dev.			
	Min.	71.4		
	Max.	71.4		
	Count	1		
Rendered Tallow to Diesel	Mean	26.56		33.24
	Std. Dev.	9.77		13.90
	Min.	19.65		16.21
	Max.	33.46		49.69
	Count	2		4

Table 3.5: Trends in carbon intensity of approved pathways over time

VARIABLES	(1) Carbon Intensity	(2) Carbon Intensity	(3) Carbon Intensity
Month of Sample	-0.0990	-0.333	-0.461
	(0.455)	(0.386)	(0.519)
Constant	71.78***	88.07***	71.78***
	(4.443)	(4.201)	(4.851)
Observations	391	391	391
R-squared	0.779	0.801	0.801
Company/Fuel	yes	.	.
Facility/Fuel	.	yes	.
Company/Facility/Fuel	.	.	yes

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

Table 3.6: Trends in carbon intensity of pending pathways over time

VARIABLES	(1) Carbon Intensity	(2) Carbon Intensity	(3) Carbon Intensity
Month of Sample	-2.071**	-2.486	-2.486
	(0.874)	(1.661)	(1.661)
Constant	32.00**	121.0***	32.00
	(15.79)	(6.77e-06)	(20.88)
Observations	227	227	227
R-squared	0.705	0.713	0.713
Company/Fuel	yes	.	.
Facility/Fuel	.	yes	.
Company/Facility/Fuel	.	.	yes

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

3.5 Chapter 3 Appendix

3.5.1 Cobb-Douglas Production

To assist with intuition, we work out parts of the model using Cobb-Douglas production functions for Y and Z. We have

$$
\begin{aligned}
& X && \text{(Dirty Input i.e. Fuel)} \\
& L && \text{(Clean Input i.e. Labor)} \\
Y &= L_Y^a X_Y^{1-a} && \text{(Intermediate Good)} \\
Z &= L_Z^b Y^c X_Z^{1-b-c} && \text{(Final Good)}
\end{aligned}
$$

In the baseline (no policy) case we assume that the upstream and downstream firm are both cost minimizers subject to meeting demand. Demand for the final good is exogenously set at $\bar{Z}$ and demand for the intermediate good is determined by the downstream firm's demand for Y. The upstream firm solves the following cost minimization problem:

$$\min_{L_Y, X_Y} \; wL_Y + p_X X_Y \tag{3.9}$$

$$s.t. \qquad \bar{Y} = L_Y^a X_Y^{1-a} \tag{3.10}$$

The resulting solution is:

$$L_Y = \left(\frac{p_X}{w}\frac{a}{1-a}\right)^{1-a} \bar{Y} \tag{3.11}$$

$$X_Y = \left(\frac{w}{p_X}\frac{1-a}{a}\right)^{a} \bar{Y} \tag{3.12}$$

If good Y is produced competitively and its price equal to marginal cost, then the price of the intermediate good is:

$$p_Y = w\left(\frac{p_X}{w}\frac{a}{1-a}\right)^{1-a} + p_X\left(\frac{w}{p_X}\frac{1-a}{a}\right)^{a} \tag{3.13}$$

The downstream firm then faces the problem:

$$\min_{L_Z,Y,Z} wL_Z + p_Y Y + p_X X \tag{3.14}$$

$$s.t. \qquad \bar{Z} = L_Z^b Y^c X^{1-b-c} \tag{3.15}$$

$$\tag{3.16}$$

The resulting first order conditions are:

$$w - \lambda b L_Z^{b-1} Y^c X^{1-b-c} = 0 \tag{FOC L}$$

$$p_Y - \lambda c L_Z^b Y^{c-1} X^{1-b-c} = 0 \tag{FOC Y}$$

$$p_x - \lambda(1-b-c) L_Z^b Y^c X^{-b-c} = 0 \tag{FOC X}$$

$$\bar{Z} = L_Z^b Y^c X^{1-b-c} \tag{FOC λ}$$

Solving this system of equations gives:

$$L_Z = \frac{p_X^{1-b-c} p_Y^c}{w^{1-b}} \frac{b^{1-b}}{c^c(1-b-c)^{1-b-c}} \bar{Z} \tag{3.17}$$

$$X_Z = \frac{p_X^{-b-c} p_Y^c}{w^{-b}} \frac{b^{-b}}{c^c(1-b-c)^{-b-c}} \bar{Z} \tag{3.18}$$

$$Y = \frac{p_X^{1-b-c} p_Y^{-1+c}}{w^{-b}} \frac{b^{-b}}{c^{-1+c}(1-b-c)^{1-b-c}} \bar{Z} \tag{3.19}$$

First Best

We know that a tax on X equal to the marginal damage will result in the efficient outcome. With a tax t, we have:

$$\begin{aligned} p_Y^t &= w\left(\frac{p_X+t}{w}\frac{a}{1-a}\right)^{1-a} + (p_X+t)\left(\frac{w}{p_X+t}\frac{1-a}{a}\right)^a \\ &= a^{-a}(1-a)^{a-1} w^a (p_x+t)^{1-a} \end{aligned} \tag{3.20}$$

and the solution above is modified by changing p_X to $p_X + t$. These simplify down to:

$$Y = \left(\frac{p_X + t}{w}\right)^{a-b-ac} a^{a(1-c)}(1-a)^{(1-a)(1-c)} \frac{b^{-b}c^{1-c}}{(1-b-c)^{1-b-c}} \bar{Z} \tag{Y^{FB}}$$

$$L_Y = \left(\frac{p_X + t}{w}\right)^{1-b-ac} a^{1-ac}(1-a)^{-c(1-a)} \frac{b^{-b}c^{1-c}}{(1-b-c)^{1-b-c}} \bar{Z} \tag{L_Y^{FB}}$$

$$X_Y = \left(\frac{p_X + t}{w}\right)^{-b-ac} a^{-ac}(1-a)^{1-c+ac} \frac{b^{-b}c^{1-c}}{(1-b-c)^{1-b-c}} \bar{Z} \tag{X_Y^{FB}}$$

$$L_Z = \left(\frac{p_X + t}{w}\right)^{1-b-ac} a^{-ac}(1-a)^{-c(1-a)} \frac{b^{1-b}c^{-c}}{(1-b-c)^{1-b-c}} \bar{Z} \tag{L_Z^{FB}}$$

$$X_Z = \left(\frac{p_X + t}{w}\right)^{-b-ac} a^{-ac}(1-a)^{-c(1-a)} \frac{b^{-b}c^{-c}}{(1-b-c)^{-b-c}} \bar{Z} \tag{X_Z^{FB}}$$

LCA Based Regulation

Lifecycle based regulation is an intensity standard on total units of X embedded in a unit of Z. For a vertically integrated firm, the goal is to minimize the production cost of Z given the intensity standard:

$$\begin{aligned} \min_{L_Y, L_Z, X_Y, X_Z} w(L_Y + L_Z) + p_X(X_Y + X_Z) \\ s.t. \qquad \bar{Z} = L_Z^b Y^c X_Z^{1-b-c} \\ Y = L_Y^a X_Y^{1-a} \\ \frac{X_Y + X_Z}{\bar{Z}} \leq \sigma \end{aligned}$$

Plugging in for Y, the Lagrangian is then:

$$\begin{aligned} L = \min_{L_Y, L_Z, X_Y, X_Z} & w(L_Y + L_Z) + p_X(X_Y + X_Z) \\ & + \lambda_1(\bar{Z} - L_Z^b(L_Y^a X_Y^{1-a})^c X_Z^{1-b-c}) + \lambda_2\left(\frac{X_Y + X_Z}{\bar{Z}} - \sigma\right) \end{aligned} \tag{3.21}$$

The first order conditions are:

$$w + \lambda_1(-acL_Z^b L_Y^{ac-1} X_Y^{(1-a)c} X_Z^{1-b-c}) = 0 \qquad \text{(FOC } L_Y\text{)}$$

$$w + \lambda_1(-bL_Z^{b-1} L_Y^{ac} X_Y^{(1-a)c} X_Z^{1-b-c}) = 0 \qquad \text{(FOC } L_Z\text{)}$$

$$p_X + \lambda_1[-(1-a)cL_Z^b L_Y^{ac} X_Y^{(1-a)c-1} X_Z^{1-b-c}] + \frac{\lambda_2}{\bar{Z}} = 0 \qquad \text{(FOC } X_Y\text{)}$$

$$p_X + \lambda_1[-(1-b-c)L_Z^b L_Y^{ac} X_Y^{(1-a)c} X_Z^{-b-c}] + \frac{\lambda_2}{\bar{Z}} = 0 \qquad \text{(FOC } X_Z\text{)}$$

$$\bar{Z} = L_Z^b L_Y^{ac} X_Y^{(1-a)c} X_Z^{1-b-c} \qquad \text{(FOC } \lambda_1\text{)}$$

$$\lambda_2 \left(\frac{X_Y + X_Z}{\bar{Z}} - \sigma \right) = 0 \qquad \frac{X_Y + X_Z}{\bar{Z}} \leq \sigma \qquad \lambda_2 \geq 0 \qquad \text{(KKT conditions)}$$

Without tradable permits, the LCA condition must be binding,

$$X_Z = \sigma \bar{Z} - X_Y \tag{3.22}$$

Dividing the labor FOCs gives

$$L_Z = \frac{b}{ac} L_Y \tag{3.23}$$

and dividing the X FOCs gives

$$X_Z = \frac{1-b-c}{(1-a)c} X_y \tag{3.24}$$

A combination of the LCA constraint and the divided X FOCs gives:

$$X_Y = \frac{(1-a)c}{1-b-ac} \sigma \bar{Z} \qquad (X_Y^{LCA})$$

$$X_Z = \frac{1-b-c}{1-b-ac} \sigma \bar{Z} \qquad (X_Z^{LCA})$$

Combing these with the FOC λ_1 gives us the solution for L_Y:

$$L_Y = \left[\left(a^b(1-a)^{-c(1-a)}\frac{b^{-b}c^{b-c+ac}(1-b-ac)^{1-b-ac}}{(1-b-c)^{1-b-c}}\right)\sigma^{-1+b+ac}\bar{Z}^{b+ac}\right]^{\frac{1}{b+ac}} \tag{L_Y^{LCA}}$$

$$L_Z = \left[\left(a^{-ac}(1-a)^{-c(1-a)}\frac{b^{ac}c^{-c}(1-b-ac)^{1-b-ac}}{(1-b-c)^{1-b-c}}\right)\sigma^{-1+b+ac}\bar{Z}^{b+ac}\right]^{\frac{1}{b+ac}} \tag{L_Z^{LCA}}$$

We can solve for what σ must be such that the LCA solution matches the first best solution:

$$\begin{aligned} X_Y^{FB} &= \left(\frac{p_X+t}{w}\right)^{-b-ac} a^{-ac}(1-a)^{1-c+ac}\frac{b^{-b}c^{1-c}}{(1-b-c)^{1-b-c}}\bar{Z} \\ &= \frac{(1-a)c}{1-b-ac}\underbrace{\left[\left(\frac{p_X+t}{w}\right)^{-b-ac} a^{-ac}(1-a)^{-c+ac}\frac{b^{-b}c^{-c}(1-b-ac)}{(1-b-c)^{1-b-c}}\right]}_{\hat{\sigma}}\bar{Z} \end{aligned}$$

We can check to see if this value for $\hat{\sigma}$ matches when plugged into the other LCA equations. For example:

$$\begin{aligned} X_Z^{LCA}(\hat{\sigma}) &= \frac{1-b-c}{1-b-ac}\left[\left(\frac{p_X+t}{w}\right)^{-b-ac} a^{-ac}(1-a)^{-c+ac}\frac{b^{-b}c^{-c}(1-b-ac)}{(1-b-c)^{1-b-c}}\right]\bar{Z} \\ &= \left[\left(\frac{p_X+t}{w}\right)^{-b-ac} a^{-ac}(1-a)^{-c+ac}\frac{b^{-b}c^{-c}}{(1-b-c)^{-b-c}}\right]\bar{Z} \end{aligned}$$

Similar equivalence can be shown for all of the other inputs. Thus an intensity standard set equal to $\hat{\sigma}$ can achieve the first best input ratio given output level $\bar{Z}$.

LCA Based Regulation With Tradable Credits

Firms may have the option to over or under comply with the LCA standard. They can generate credits or purchase credits to meet the standard and face the following problem:

$$\begin{aligned}\min_{L_Y,L_Z,X_Y,X_Z,Y} w(L_Y + L_Z) + p_X(X_Y + X_Z) + p_R R \\ s.t. \qquad \bar{Z} = L_Z^b Y^c X_Z^{1-b-c} \\ Y = L_Y^a X_Y^{1-a} \\ \frac{X_Y + X_Z - R}{\bar{Z}} \leq \sigma\end{aligned}$$

Where R denotes the number of credits the firm has to purchase (or creates) and P_R is an exogenously determined price of a credit. The first order conditions for the minimization problem with a binding standard are:

$$w + \lambda_1(-acL_Z^b L_Y^{ac-1} X_Y^{(1-a)c} X_Z^{1-b-c}) = 0 \qquad \text{(FOC } L_Y\text{)}$$

$$w + \lambda_1(-bL_Z^{b-1} L_Y^{ac} X_Y^{(1-a)c} X_Z^{1-b-c}) = 0 \qquad \text{(FOC } L_Z\text{)}$$

$$p_X + \lambda_1[-(1-a)cL_Z^b L_Y^{ac} X_Y^{(1-a)c-1} X_Z^{1-b-c}] + \frac{\lambda_2}{\bar{Z}} = 0 \qquad \text{(FOC } X_Y\text{)}$$

$$p_X + \lambda_1[-(1-b-c)L_Z^b L_Y^{ac} X_Y^{(1-a)c} X_Z^{-b-c}] + \frac{\lambda_2}{\bar{Z}} = 0 \qquad \text{(FOC } X_Z\text{)}$$

$$p_R - \frac{\lambda_2}{\bar{Z}} = 0 \qquad \text{(FOC R)}$$

$$\bar{Z} = L_Z^b L_Y^{ac} X_Y^{(1-a)c} X_Z^{1-b-c} \qquad \text{(FOC } \lambda_1\text{)}$$

$$\frac{X_Y + X_Z - R}{\bar{Z}} = \sigma \qquad \text{(FOC } \lambda_2\text{)}$$

Plugging in for λ_2 and dividing the first order conditions by themselves gives the following relationships:

$$L_Z = \frac{b}{ac} L_Y \qquad \text{(L/L)}$$

$$X_Z = \frac{1-b-c}{(1-a)c} X_Y \qquad \text{(X/X)}$$

$$X_Y = \frac{1-a}{a} \frac{w}{p_X + p_R} L_Y \qquad \text{(Ly/Xy)}$$

$$X_Z = \frac{1-b-c}{b} \frac{w}{p_X + p_R} L_Z \qquad \text{(Lz/Xz)}$$

and combining these with the LCA constraint and the production constraint gives the solutions:

$$L_Y = a^{1-ac}(1-a)^{-c(1-a)} \frac{b^{-b}c^{1-c}}{(1-b-c)^{1-b-c}} \left(\frac{w}{p_X + p_R}\right)^{-1+b+ac} \bar{Z} \tag{L_Y^R}$$

$$L_Z = a^{-ac}(1-a)^{-c(1-a)} \frac{b^{1-b}c^{-c}}{(1-b-c)^{1-b-c}} \left(\frac{w}{p_X + p_R}\right)^{-1+b+ac} \bar{Z} \tag{L_Z^R}$$

$$X_Z = a^{-ac}(1-a)^{-c(1-a)} \frac{b^{-b}c^{-c}}{(1-b-c)^{-b-c}} \left(\frac{w}{p_X + p_R}\right)^{b+ac} \bar{Z} \tag{X_Z^R}$$

$$X_Y = a^{-ac}(1-a)^{1-c(1-a)} \frac{b^{-b}c^{1-c}}{(1-b-c)^{1-b-c}} \left(\frac{w}{p_X + p_R}\right)^{b+ac} \bar{Z} \tag{X_Y^R}$$

$$R = \left[\sigma - a^{-ac}(1-a)^{-c(1-a)} \frac{b^{-b}c^{-c}(1-b-ac)}{(1-b-c)^{1-b-c}} \left(\frac{w}{p_X + p_R}\right)^{b+ac}\right] \bar{Z} \tag{R^R}$$

These quantity of L's and X's match the first best cost minimization values, for fixed $\bar{Z}$, if $p_R = t$. Firms will demand the same inputs as they would under a tax and then make up the difference from the standard by purchasing permits.

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