The Short-Run Price Elasticity of Gasoline Demand In Major American Cities:

Can Changes in Urban Form Affect Gasoline Demand?

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1. Introduction

There has been growing concern in the past decade about global warming and fossil fuel dependence. One focus has been to curb the gasoline consumption caused by driving. Urban characteristics, such as mass transit usage and density, might affect how much people choose to drive. Many believe that better urban planning can reduce American dependence on gasoline. If the demand for gasoline is indeed very inelastic, perhaps redesigning cities in a manner that increases the short-run price elasticity of gasoline demand might reduce gasoline demand in the face of permanently higher prices.

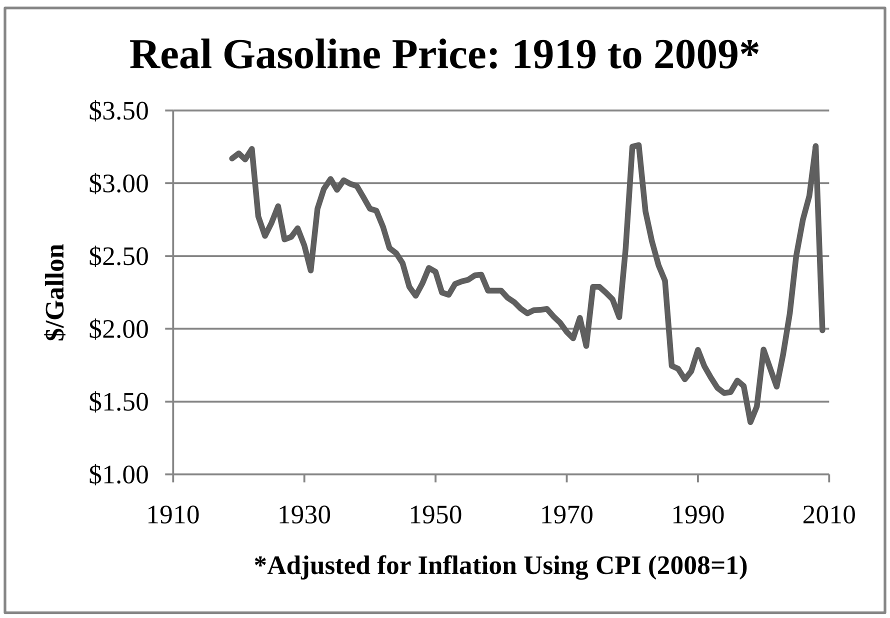

Figure 1.1

The majority of previous estimations of gasoline demand have used older data from the late 1970s and early 1980s, focusing on the price shocks from that period. However, recently the United States has experienced another large gasoline price shock. Between mid-July in 2003 and mid-July in 2008, the average price of gasoline in the United States rose from roughly $1.50 per gallon to over $4.10 per gallon. Figure 1.1

shows the price of gasoline in real terms historically. The graph illustrates that the recent price shock starting in 2003 is as extreme, if not more so, than the shock in the late 1970s. Estimations made more recently, using more current data, have found the price elasticity of gasoline demand to be much more inelastic than previously expected. The recent price shock provides updated price variation that can be used to better estimate how urban form, or the organization of cities, might affect gasoline demand in large cities in the United States.

In this paper, I investigate the extent to which variations in use of mass transit and urban density explain regional differences in gasoline demand. Newer, western cities use mass transit less, partly due to sprawl and partly due to poorer transit systems. However, this might be endogenous to the cities and those who choose to live there. If the inclusion of variables for mass transit use or for the density of particular cities explain more of the differences between regions than other explanatory variables, it would provide evidence that increasing mass transit use or increasing the density of cities might increase the price elasticity of gasoline demand in the short-run.

It is also possible that regional differences in gasoline demand can be explained by differences in the characteristics of the populations. Personal preferences are important for determining gasoline demand, but hard to capture. Those who live in newer, western cities that are more spread out might have a personal preference to live in a city where driving is more necessary than those living in denser cities. The majority of Americans do not move very far from where they are born, thus most of those living in sprawling cities likely grew up in a similar environment, leading them to view driving a car as more of necessity than those who grew up in denser regions. Larger explanatory power from variables such as whether the family possessed two or more cars, or whether they owned a truck would be indicators of behavior with a preference towards driving.

I find the short-run price elasticity of gasoline demand in cities over 500,000 to be .279 in the West Coast, .337 in the Gulf Coast, .243 in the Midwest, and .378 in the Central Atlantic. While the result for the Central Atlantic region is in line with its density and mass transit, the Midwest is surprisingly inelastic and the Gulf Coast is surprisingly elastic relative to the other regions. The estimates are more elastic than previous estimates for the country as a whole; however, this could be attributed to urban driving habits which are thought to be more elastic than rural habits. When I do not control for city size, I find an average price elasticity of .140, which is only slightly more elastic than the recent estimate of Hughes et al. (2008) of .03 to .07. Further, while density and mass transit changes do affect the price elasticity of gasoline demand, the price elasticity is largely insensitive to changes. This suggests that if a population initially had relatively inelastic gasoline demand, even if density and usage of mass transit were increased to levels similar to regions such as the Central Atlantic, it would still relatively inelastic. There appear to be intrinsic differences in personal preferences for gasoline consumption between the regions.

The rest of the paper is organized as follows: Section 2 introduces the theory and past literature related to urban form; it then further explains how urban form affects driving habits and how estimations of the price elasticity of gasoline demand have been made previously. Section 3 presents the regression equations and the data used. Section 4 presents the results. Section 5 concludes.

2. Literature Review

2.1 Urban Form

Newman and Kenworthy (1999) provide a background on how cities have developed over time. There are large differences in how cities are organized because of the technology available at the time that the city was planned. Understanding these differences is extremely important for understanding how older East Coast cities might have more elastic short-run gasoline demand than newer Western cities.

The general premise that Newman and Kenworthy (1999) present, is that people are generally willing to travel thirty minutes to a destination they have to visit commonly. In cities before the industrial revolution, this was accomplished by walking, leading to narrow, winding streets. During the industrial revolution, however, most of the major American cities east of the Mississippi were developed. At this time they could develop using mass transit to increase the size of the city. The continued constraint of thirty minute accessibility, though, led any new growth in the city to develop right along the mass transit lines, which radiated from the city like spokes on a wheel. Each of these new developments maintained similar characteristics to the “walking city”, clustered around the mass transit stations. (Newman and Kenworthy, 1999, pg. 28ff) Variation in the density of cities can therefore be assumed to be exogenous, because it is dependent more on when the city was created than on the population currently living there.

The automobile shaped the newer cities that developed mostly after the Second World War in the United States. Instead of requiring higher density development around central transportation hubs so that people could walk to them from home, the automobile allowed development to be much less dense. The assumption was that people would own cars and drive to any destination they needed to visit. The process created cities that were dependent upon cars because their development was spread out and decentralized, creating a problem for any sort of mass transit solution that might be attempted later.

Newman and Kenworthy find that the American cities as a whole use cars for transportation far more than cities in other countries because of their sprawling nature. (Newman and Kenworthy, 1999, pg. 113) Further, amongst American cities, newer cities were found to use roughly twenty percent more gasoline for private transit than older cities in 1990, providing evidence that the organization of cities might have an effect on driving habits.

2.1a Urban Form and Driving Habits

Differences in the populations that reside in the Eastern and Western cities need to be controlled to capture the variation in gasoline demand related to density and the use of mass transit. There is a wide literature that has looked at how city and neighborhood organization affects commuter behavior, largely with the goal of determining how changes in urban form might reduce gasoline use. The literature provides information on how regional differences and demographic factors affect driving habits. Regional differences include city density and mass transit use, while demographic factors include family size, number of earners, and education level. Much of the literature, however, also finds that personal choice largely influences living situations. This implies that changes in urban form will likely have a smaller effect on travel than initially predicted.

Density and mass transit use are very important factors to consider when discussing how urban form affects travel choices. Handy (1996), Kahn (2000), Giuliano and Narayan (2003), Bento et al. (2005), and Grazi et al. (2008) all find that density is at least a useful measure of transit availability. One could therefore use density as a rough substitute for other transit measures, such as the distance to the nearest transit stop, which might suffer from endogeneity. Households that have a preference for taking mass transit would choose to locate near a stop, whereas those that did not might locate elsewhere. Further, while Bento et al. (2005) find that distance to a transit stop significantly affects demand for car travel, the explanatory power of this variable is greatly reduced when New York is removed. After looking at US cities with over 500,000 people, the density of the city appeared highly correlated with mass transit use (roughly 85 percent). More importantly, density appears to have an effect on vehicle miles traveled, in Kahn (2000) and Grazi et al. (2008), who both use density to explain differences in gasoline demand.

Demographic information is typically helpful as a proxy for how personal preferences might affect gasoline consumption. In order to control for people choosing to live in different areas as a result of personal preferences, Grazi et al. (2008) instrument location choice with several demographic variables. The authors argue that families with children of the same gender are more likely to live in areas of higher density, because the children can be housed in the same room. Having a larger number of children will cause families to be more likely to live in lower density areas and thus drive more. I do not control for the gender of children due to data unavailability, although I do control for the number of children. Bento et al. (2005) also explores the impact of household demographics on driving behavior. Their paper finds that simply adding a working female adult or a young adult (17-21) to the household increases the miles traveled by the household as a whole by roughly 5,000 miles per year. I add a variable for whether both spouses work in a particular household to try and capture this variation. Household demographic information, such as number of children, the ages of the children and their parents, and whether one or two adults are working should therefore add explanatory power to the regression.

Another important demographic control is the level of education. One of the more notable changes that has taken place in the United States with the advent of the computer has been the possibility of working from home. The ability to telecommute has taken the car almost entirely out of the picture for some people in relation to their work. Workers now have the option to simply not travel to work in the face of higher gasoline prices and instead work from home. While this solution is available for all regions of the country, it is not usually available for all demographics. Tang et al. (2008) finds that a higher education level is significant when determining whether someone will choose to work from home. Workers who have higher education are usually more likely to use computers to accomplish their jobs and need less supervision, making telecommuting more feasible for them than for less educated workers. Higher education then, should lead to a more elastic demand for gasoline. I control for this by adding a dummy variable which depends on whether the head of household has at least received a college degree.

Most of the papers discussing the organization of cities and their effects on driving habits used the Nationwide Personal Travel Survey (NPTS), including Kahn (2000), Giuliano and Naravan (2003), and Bento et al. (2005). The data set is useful for determining differences in the miles driven between metropolitan areas, but because it is not a time-series data set, estimations of the elasticity of demand can not be made. The NPTS reports driving by vehicle miles traveled per year, instead of gasoline expenditures, which is reported by the Panel Study of Income Dynamics on a monthly level. Vehicle miles traveled does not vary entirely inversely with the price of gasoline; a study by the National Transportation Board found that drivers were reducing their speed in order to achieve increased fuel economy. Drivers are surely resorting to other changes in driving behavior to reduce their fuel expenditures that do not show up in vehicle miles traveled.

2.2 Estimations of the Price Elasticity of Gasoline Demand

The price elasticity of gasoline demand received a large amount of attention following the oil price shocks at the end of the 1970s and early 1980s. Much of the past research on the price elasticity of gasoline demand has focused on this period; I however look at more recent data. Estimates from this period usually find the short-run price elasticity of gasoline demand to be around .23 (Espey 1998). In the past several decades, though, there has been large growth in the western regions of the country and a movement from the city centers to suburbs, which could have altered short term gasoline demand. For example, Kahn (2000) found that suburbanites drive 31 to 35 percent more than those dwelling within cities. Despite the possibility that most of the gasoline demand estimations based upon older data are outdated, they still provide a wealth of information on how best to estimate the price elasticity of gasoline demand using more recent data because of the similarity in methodology. [1]

[1] More recent papers by Small and Van Dender (2006) and Hughes et al. (2008), who estimated the price elasticity of gasoline demand to be around .03 to .07, have shown the short-run price elasticity to be much more inelastic than estimates relying on older data.

When estimating gasoline demand, studies differ by whether aggregate or individual household data are used. According to the meta-analysis by Espey (1998), of the over 300 estimations of the short-run price elasticity of gasoline demand, roughly 40 percent of the estimations used aggregate data, while 60 percent used per capita or household data. Moreover, when using household data, studies either use vehicle miles traveled or gasoline expenditures to examine how consumption changes over time.

While consumer level data at the household or per capita level appears to be preferable, many recent studies such as Small and Van Dender (2006) and Hughes et al. (2008) have focused more on aggregate data. The main reason is that aggregate data are easier to obtain, especially when comparisons are made between past gasoline demand, in the late 1970s, and more recent gasoline demand in the past decade. Kayser (2000), however, uses the panel data from the Panel Study of Income Dynamics (PSID), in the belief that panel data provides a better picture of how individual characteristics affect demand. It appears that while consumer level data are easier to work with, the estimates from Kayser (2000) and Hughes et al. (2008) are very similar even though one uses aggregate data and the other uses household data. Since more recent data are now available from the PSID, covering part of the price run-up from 2003-2008, I will use household data, focusing on the years 2003 to 2005.

Espey (1998) provides a good summary of the earlier work done on gasoline demand through meta-analysis. She finds that a good estimate of the short-run price elasticity of gasoline demand for the period of the late 1970s and early 1980s is -.23, using the median of the over 300 estimations surveyed. Further she finds that while linear and log linear estimations estimate roughly the same price elasticities of gasoline demand, linear estimations are found to be insignificant. Kayser (2000) does not support the reasoning, finding that there is no difference between a linear and log-linear model using a Box-Cox test, but makes the decision to use a log linear model in light of Archibald and Gillingham (1980) using one. Hughes et al. (2008) also adopts the log-linear model, because of its fit with the data and easy comparison with previous studies. The log-linear model in the form of equation 1 therefore appears the most appropriate for my estimations:

$$lnGAS_{it} = \beta_0 + \beta_1 lnP_t + \varepsilon_{it} \qquad (1)$$

Where lnGAS is the natural logarithm of gasoline expenditures in a particular period t, for a particular household i, and P is the price of gasoline in that period.

No matter the type of regression being run, the importance of including the level of income for the consumer is universally agreed upon. Kayser (2000) points out in his paper, that because gasoline expenditure makes up a larger portion of total expenditures for poorer households, any change in the price of gasoline will have a larger effect on poor households. At the same time, more of the driving done by wealthier consumers will be discretionary driving, which is more easily reduced than something like a work commute. An increase in income would then be associated with a more elastic short-run gasoline demand. In similar fashion to Archibald and Gillingham (1980), Kayser includes an interaction term between income and the price of gasoline, to allow the elasticity to vary over income levels.

Controls for the difference between rural and urban driving habits also have been added in many models. Given the much lower population density in rural areas and lack of alternative transportation, it makes sense that rural areas would have different elasticities of gasoline demand than cities. Further, people in urban areas are more likely to drive smaller, more fuel efficient cars than those in rural areas who are more likely to own trucks. Small and Van Dender (2006) control for this difference by using a variable that controls for urbanization. While they find that the coefficient is small, it is significant. For my regressions I will be solely looking at urbanized areas, because of the increased density, I expect short-run elasticity estimates to be slightly more elastic than estimates for the country as a whole.

2.2a Estimating the *Short-Run* Price Elasticity of Gasoline Demand

While some studies have found it important to estimate medium and long run demand for gasoline, differences in gasoline demand between older and newer cities in the United States will most likely be larger in the short-run. When the price of gasoline rises rapidly, those in older, denser cities, which are more often served by better mass transit, can more easily switch to alternative means of transportation in the face of a price shock. In the longer run, though, those living in older, eastern cities and newer western cities can change their vehicle choice or even job location, leading any differences between cities to be far less perceptible. Given this caveat, factors to be included in any regression need to try and limit the ability of the consumer to change location and their vehicle choice, in order to capture the short-run gasoline demand.

Espey’s (1998) meta-analysis determined that for any estimate of the price elasticity of gasoline demand to capture the shortest term demand, both vehicle ownership and the fuel efficiency of the vehicle would need to be included. Small and Van Dender (2006) also include an estimate of vehicle stock in their regressions. Further, from other papers, the number of vehicles in a particular household appears to affect the amount that the household drives. Bento et al. (2005) explain the importance of the size of the vehicle stock by noting that any increases in the last two decades in the amount of driving have largely come from increases in the number of vehicles owned. Archibald and Gillingham (1980) go so far as to offer separate estimates of gasoline demand, based upon whether the family in question is a single or multicar family. Although their estimations of gasoline demand for the two types of consumers are almost identical, the car stock cannot be ignored.

Even when estimating the shortest-term gasoline demand, a lag appears to add explanatory power. When consumers fill up their tanks, they are doing so in response to their driving habits in a previous time period. Once they realize their higher gasoline expenditures per fill up, they can then alter their driving habits in anticipation of continuing to pay more for gasoline. For example, Hughes et al. (2008) found that it took consumers roughly one and half months to adjust to price changes in the short run, when using a one month lag. I lag my price data by a month to try and capture this effect. Small and Van Dender (2006) also employed a lagged effect on their model to account for the frictions caused by a change in price.

3. Empirical Methodology and Data

3.1 State Estimation

I look first at state differences in the short-run price elasticity of gasoline demand for all households, not just those in cities, so that the price elasticity can be estimated for the entire state. Obtaining estimations for the price elasticities in different states allows me to create a map of the United States with gasoline demand color-coded by state. This visual representation illustrates how the price elasticity of gasoline demand varies when looking at areas of the United States as a whole, so any regional differences that are not solely the result of city characteristics can be seen. The first estimation then will be in the form of equation 2, a log-linear model as discussed in section 2.3:

$$lnGAS_{it} = \beta_1 + \beta_2 lnP_t + \beta_3 lnTOTINC_{it} + \beta_4 lnP_t lnTOTINC_{it} + \beta_a S + \beta_b lnP_{it} * S + \beta_c lnP_{it} lnTOTINC_{it} * S + \varepsilon_i + \nu_{it} \qquad (2)$$

where i represents an individual household and t represents time. The regression covers households interviewed in 2003 and 2005. I use the natural logarithm of gasoline expenditures, lnGAS, in a particular month as the dependent variable. The regression explains how variations in the price of gasoline in a particular month, given by lnP, affect gasoline expenditures.

I control for income as my sole demographic variable, with the expectation that it would have the most explanatory power, as the previous literature has shown. To control for income I used the natural logarithm of total income in the previous year, lnTOTINC, with the expectation that consumers will plan expenditures in accordance with income in the past. Income was then interacted with the price of gasoline to allow the short-run price elasticity of gasoline to vary across income levels. State dummies are represented by variable S. The short-run price elasticities for individual states then can be obtained by using the coefficients of lnP, lnPlnTOTINC, the state interaction terms and the mean values for income in each state.

Household data for the state regression and the regional regression, discussed next, was obtained from the Panel Study of Income Dynamics (PSID). The use of household data allows me to ignore the possibility of a simultaneity issue, which would have been present had aggregate data been used. Specifically, although the price of gasoline is determined by the intersection of the supply and demand curves, households are a small enough unit that we can consider them as price-takers, and thus have no effect individually on the demand curve. Therefore the price of a gallon of gasoline will not be influenced by individual household expenditures. Data were available specifically for gasoline expenditures most recently from 2003 and 2005. [2] While this period did not experience the most dramatic changes in gasoline price, prices did increase roughly one dollar per gallon in nominal terms.

3.2 Regional Estimation

The main estimation of price elasticity of gasoline demand will look at differences in gasoline demand amongst major American cities from a regional level. The regions of the West Coast, Gulf Coast, Midwest, and Central Atlantic will be used, both because of their differences in demographics and urban form, and the large number of respondents

[2] PSID data from 2007 will not be available until the fall of 2009.

from them. For a list of states in each region, see Table A.2 in the Appendix. The estimation of the price elasticity of gasoline demand will be accomplished using a log-linear model, of similar form to equation 3

$$lnGAS_{it} = \beta_1 + \beta_2 lnP_t + \beta_a R + \beta_b lnP_t(R) + \beta_c lnP_t(D_{it})$$
$$+\beta_d lnP_t(R)(D_{it}) + \varepsilon_i + \nu_{it} \qquad (3)$$

Household data from 2003 and 2005 were included in the regression.

Also included is a region dummy, R, (the Midwest being the excluded dummy), and variables, D, representing information on demographics and city characteristics; information that varies by household and by region. The demographic variables included in D are dummies for TWOCAR, if the household owns two or more cars, TRUCK, if the household owns a truck, COLGRAD, if the head of household graduated from college, BLACK, if the head of household is black, and BW, if both the head of the household and their spouse work. The variable CHIL is also included, representing the number of children in the household. The expected signs for the variables from the regression are provided in Table 3.1.

Table 3.1: Expected Regression Coefficients

Variable	Reason	Expected Sign*
MTRANS	More mass transit creates easier opportunities to switch away from driving	-
DEN	Density is highly correlated with mass transit, higher density also reduces the need for car trips	-
TOTINC	At higher income levels, more car trips are discretionary, gasoline expenditures are also smaller proportion of income	+/-
TWOCAR	Having a larger vehicle stock allows drivers more room to reduce driving, also one vehicle might achieve better mileage	-
TRUCK	Any increase in gasoline prices will effect trucks and SUVs more because of worse mileage	-
COLGRAD	Having a college degree is positively correlated with higher income, however it also allows the possibility of working from home	-
BLACK	Past papers have found that minorities typically drive less, therefore less of the driving is probably discretionary and harder to reduce	+
BW	Both spouses working lead to more necessary driving	+
CHIL	Children lead to more necessary driving	+

*(+ leads to more inelastic demand)

The variables included for vehicle choice, TWOCAR and TRUCK, provide a control for vehicle stock. I expect that having a larger vehicle stock, for instance having two or more cars, would allow the household more choice in reducing gasoline consumption. Therefore, I expect the sign of the coefficient in the regression to be negative. If the household decides to have a truck or SUV, they will be affected more by any rises in gasoline price, because their vehicle would on average have worse mileage. The sign of the coefficient would then be negative as well.

Other variables for demographic information like COLGRAD, BLACK, BW, and CHIL, control for differences in the demographics of households in the different regions. If the head of household has a college education, they most likely will be in a better position to telecommute in the face of higher gas prices. These households then would have a more elastic demand for gasoline, leading the sign of the coefficient to be negative. Further, studies have found that black households generally drive less than white households with similar demographic characteristics, Bento et al. (2005). Therefore, less of the driving might be discretionary, making it harder to reduce and leading to more inelastic demand and a positive coefficient. If the spouse of the head of household works as well, this would probably lead to less of the driving being discretionary, making driving harder to reduce and gasoline demand more inelastic. The sign of the coefficient would then be positive. Having more children would decrease the likelihood of living in a dense region, leading to more inelastic gasoline demand. While density is already controlled for, variables like the number of children help to reduce variations in where people live as a result of personal preferences. Further, an increase in the number of children would also lead to less of the driving being discretionary, also making the sign of the coefficient negative.

Further, I include variables for the natural logarithm of income in the past year, lnTOTINC, the percentage of the population using mass transit in a particular city, MTRANS, and the natural logarithm of the density in the county the city is located in, lnDEN. The interaction between income and gasoline price helps to control for economic expansions and contractions, which might affect gasoline demand dependent on economic conditions in a particular year. The sign of the coefficient for income is ambiguous. While more trips are discretionary at higher income levels, gasoline expenditures are also a smaller proportion of income. The percentage of the population using public transportation (excluding taxis) estimates the level of mass transit in a particular city. The higher the level of mass transit use, the more relative ease one could expect when trying to shift away from driving. Therefore, I expect the coefficient for mass transit to be negative. Any increases in density will most likely lead to reductions in the amount of necessary driving, because of density's high correlation with mass transit.

The price elasticity of a particular household is determined by adding the coefficients of lnP and its interaction terms along with particular household values for the demographic variables, region, mass transit availability, and the density of the city in which the household resides. To control for city size, the regression was only run on households reporting that they resided in counties with cities larger than 500,000 people. The regression was also run for the four regions without the Beale urban-rural control to help compare variations in short run gasoline demand outside of large cities and simply in the regions as a whole. Both regressions were run using random effects. The results are similar, but less significant for regular OLS with fixed effects.

3.3 Data and Summary Statistics

The summary statistics follow in Table 4. The list of variables and their sources, states included in each region, and correlations between household variables are included in Tables A.1-A.3 in the Appendix.

The Panel Study of Income Dynamics (PSID) provides far reaching information on household consumption levels and characteristics. As a representative sample of households within the United States it also easily allows comparisons between regions and states. Data were available for gasoline expenditures most recently from 2003 and 2005. While this period did not experience the most dramatic changes in gasoline price, prices did increase roughly one dollar per gallon in nominal terms. A key variable available from the PSID is the level of gasoline expenditures in a particular month, used to model gasoline consumption. Unfortunately age information on the children in the household was unavailable, so this was not added as a variable. I believe this reduces the explanatory power of children for gasoline demand, as most papers only find that children around driving age have a significant effect on gasoline demand.

Table 3.2: Average Gas Prices For Selected States[a]

State	Year		
	2003	2005	2005[c]
California	$1.88	$2.52	
Colorado	$1.57	$2.30	
Florida[b]	$1.58	$2.36	$2.50
Massachusetts[b]	$1.63	$2.31	$2.48
Minnesota	$1.54	$2.17	
New York	$1.73	$2.45	
Ohio[b]	$1.54	$2.25	$2.38
Texas	$1.49	$2.22	
Washington[b]	$1.68	$2.41	$2.56

a: Prices are for the average retail price of a gallon of gasoline
b: Prices for 2003 only available May 26 onwards
c: Prices for May 26, 2005 onwards
Source: Energy Information Administration

One of the key variables for any regression on the price elasticity of gasoline demand is the actual price of gasoline. Historical gasoline price data were obtained from the Energy Information Administration. Price data were unavailable historically for all states, so gasoline prices by region, on a monthly average (to reflect the expenditure period), were used. Therefore, if a more inelastic demand for gasoline prices in California relative to New York led prices to rise more in California, this would be accounted for in the regression. Prices were controlled for inflation using GDP deflators from the Bureau of Economic Analysis. Some price data, uncontrolled for inflation, are given in Table 3.2, for selected states where retail price data were available. The table highlights differences in gasoline prices between 2003 and 2005, as well as the differences present across states. Two columns are given for 2005, so that accurate comparisons may be made for some states, where gasoline data were only available for the second half of the year.[3]

Data for the level of mass transit in a particular Metropolitan Statistical Area (MSA) were obtained from the US Census. Data for the density of a particular MSA were found using US Census data on the size, in square miles, of the city and its population. These data were then correlated with the PSID data at a state level, using Beale urban-rural codes from the PSID, so that only counties containing cities greater than 500,000 persons would be included. There is some error in this approach, as certain states contain more than one city of this size (in California for instance, San Diego, Los Angeles, San Jose, and San Francisco all fit this criterion). Each state was thus matched with aggregated density and mass transit data, weighted by the size of the cities in a particular state, using Census data on county size. The density and mass transit use of a larger city, like Los Angeles, then receives more weight than a smaller city, like San Diego, to reflect the differing probabilities of the respondent being from either city.

[3] The state regression was also run with this data, the results are not shown, but were essentially the same.

Table 3.3: Summary Statistics

All Respondents - 2003, 2005	variable	obs	mean	median	sd	min	max
All Regions	DEN	22742	1421.05	981.00	1311.97	255.00	9316.90
	MTRANS	22742	0.14	0.10	0.13	0.02	0.55
	TOTINC	38872	66492.26	51204.98	84087.99	-932361.10	5024575.00
	TWOCAR	38872	0.70	1.00	0.46	0.00	1.00
	TRUCK	38872	0.48	0.00	0.50	0.00	1.00
	COLGRAD	35265	0.27	0.00	0.44	0.00	1.00
	BLACK	35265	0.29	0.00	0.45	0.00	1.00
	BW	38872	0.51	1.00	0.50	0.00	1.00
	CHIL	38872	1.32	1.00	1.30	0.00	7.00

Respondents, Cities >500,000	variable	obs	mean	median	sd	min	max
All Regions	DEN	8212	1424.82	981.00	1569.91	255.00	9316.90
	MTRANS	8212	0.13	0.10	0.12	0.02	0.55
	TOTINC	9322	69541.86	51637.92	111389.80	-5758.88	5024575.00
	TWOCAR	9322	0.59	1.00	0.49	0.00	1.00
	TRUCK	9322	0.38	0.00	0.49	0.00	1.00
	COLGRAD	8332	0.26	0.00	0.44	0.00	1.00
	BLACK	8332	0.44	0.00	0.50	0.00	1.00
	BW	9322	0.48	0.00	0.50	0.00	1.00
	CHIL	9322	1.40	1.00	1.32	0.00	6.00
Central Atlantic	DEN	1109	2871.28	1380.00	2798.04	1022.00	9316.90
	MTRANS	1109	0.35	0.26	0.15	0.20	0.55
	TOTINC	1371	77365.45	58099.38	132240.10	287.94	2019638.00
	TWOCAR	1371	0.48	0.00	0.50	0.00	1.00
	TRUCK	1371	0.25	0.00	0.43	0.00	1.00
	COLGRAD	1192	0.22	0.00	0.41	0.00	1.00
	BLACK	1192	0.56	1.00	0.50	0.00	1.00
	BW	1371	0.48	0.00	0.50	0.00	1.00
	CHIL	1371	1.33	1.00	1.20	0.00	5.00
Midwest	DEN	2701	1473.39	687.00	1601.97	441.00	6212.00
	MTRANS	2701	0.11	0.09	0.07	0.02	0.25
	TOTINC	2721	59425.58	46043.38	55779.20	479.91	737222.50
	TWOCAR	2721	0.54	1.00	0.50	0.00	1.00
	TRUCK	2721	0.32	0.00	0.47	0.00	1.00
	COLGRAD	2469	0.22	0.00	0.41	0.00	1.00
	BLACK	2469	0.49	0.00	0.50	0.00	1.00
	BW	2721	0.44	0.00	0.50	0.00	1.00
	CHIL	2721	1.57	1.00	1.47	0.00	6.00
Gulf Coast	DEN	1232	522.00	522.00	0.00	522.00	522.00
	MTRANS	1232	0.05	0.05	0.00	0.05	0.05
	TOTINC	1340	63221.24	45488.40	144371.30	-5758.88	5024575.00
	TWOCAR	1340	0.57	1.00	0.50	0.00	1.00
	TRUCK	1340	0.44	0.00	0.50	0.00	1.00
	COLGRAD	1176	0.22	0.00	0.42	0.00	1.00
	BLACK	1176	0.61	1.00	0.49	0.00	1.00
	BW	1340	0.47	0.00	0.50	0.00	1.00
	CHIL	1340	1.62	2.00	1.31	0.00	6.00
West Coast	DEN	2306	1278.94	1670.00	608.13	255.00	1670.00
	MTRANS	2306	0.10	0.11	0.04	0.04	0.18
	TOTINC	2364	81538.58	57554.22	146323.00	0.00	3513538.00
	TWOCAR	2364	0.69	1.00	0.46	0.00	1.00
	TRUCK	2364	0.48	0.00	0.50	0.00	1.00
	COLGRAD	2137	0.30	0.00	0.46	0.00	1.00
	BLACK	2137	0.24	0.00	0.42	0.00	1.00
	BW	2364	0.51	1.00	0.50	0.00	1.00
	CHIL	2364	1.26	1.00	1.28	0.00	6.00

Source: DEN and MTRANS data from US Census; all other variables from 2003 and 2005 PSID

Differences between the regions appear readily after looking at the summary statistics in Table 3.3. As expected, the Central Atlantic is by far the densest region at over 2,800 people per square mile, with the Gulf Coast being the most sprawling at just under 525 people per square mile. The Midwest and West Coast are roughly equally dense. Similar differences appear between the regions when looking at mass transit usage, with the Central Atlantic again having the most. The average income in each region also highlights differences, with both the Central Atlantic and West Coast having highest household incomes on average, roughly $80,000 per year. The Midwest had the lowest household income at just above $59,000 per year, slightly below that of the Gulf Coast.

In the West Coast, almost 7 out of 10 households have cars, compared with less than 5 out of 10 in the Central Atlantic. In the West Coast and Gulf Coast roughly 4 to 5 out of every 10 households own trucks or SUVs and only 2 to 3 out of every 10 households own trucks or SUVs in the Central Atlantic or Midwest.

Demographically, there appears to be slightly fewer variations between regions. 22 percent of households are headed by college graduates in all regions except the West Coast where 30 percent are college graduates. Looking at the percentage of households headed by those who are black, the West Coast is an outlier as well, with only 24 percent. The other regions are all more than double that, falling between 49 and 61 percent. All of the regions are roughly equal for the percentage of households with both adults working, roughly half fit the category. The Midwest is a slight outlier with only 44 percent of households. There are also differences in the average number of children per household.

The Midwest and Gulf Coast have the most, roughly 1.6 children per household, while the West Coast and Central Atlantic have the least, at roughly 1.3 children per household.

Table 3.4: Household Variable Correlations[a]

	Correlation	GASEXP	TWOCAR	TRUCK	COLGRAD	BLACK	WW	CHIL
All Regions[b]	TWOCAR	0.3216						
	TRUCK	0.2441	0.3376					
	COLGRAD	0.0380	0.1201	0.0385				
	BLACK	-0.0574	-0.2436	-0.1905	-0.1902			
	BW	0.1953	0.3978	0.1724	0.0803	-0.2039		
	CHIL	0.0693	-0.0106	0.0107	-0.1291	0.1828	-0.0186	
	TOTINC	0.1142	0.1866	0.0928	0.1826	-0.1650	0.1532	-0.0596
Central Atlantic	TWOCAR	0.3625						
	TRUCK	0.3327	0.2956					
	COLGRAD	-0.0623	0.1063	0.0008				
	BLACK	-0.0450	-0.1084	-0.1032	-0.2340			
	BW	0.1872	0.2973	0.1407	0.0154	-0.2758		
	CHIL	0.0962	0.0018	0.0227	-0.1128	0.1839	0.0668	
	TOTINC	0.1510	0.1342	0.1268	0.3839	-0.3392	0.2141	0.0564
Midwest	TWOCAR	0.2991						
	TRUCK	0.1797	0.2810					
	COLGRAD	0.0456	0.1559	0.0875				
	BLACK	-0.0200	-0.2585	-0.2000	-0.2302			
	BW	0.2173	0.5076	0.1849	0.2005	-0.2392		
	CHIL	0.0200	-0.0148	0.0142	-0.1160	0.1700	-0.0547	
	TOTINC	0.2473	0.3996	0.1895	0.3421	-0.2763	0.3951	-0.1191
Gulf Coast	TWOCAR	0.3991						
	TRUCK	0.1804	0.3699					
	COLGRAD	0.0237	0.1120	0.0362				
	BLACK	-0.1501	-0.2048	-0.2374	-0.1030			
	BW	0.1985	0.3401	0.1619	0.2204	-0.1012		
	CHIL	-0.0265	-0.1306	-0.0414	-0.1738	0.1518	-0.0390	
	TOTINC	0.1198	0.1213	0.1017	0.0555	-0.1178	0.1084	-0.0717
West Coast	TWOCAR	0.2743						
	TRUCK	0.2689	0.3553					
	COLGRAD	0.0518	0.0563	-0.0281				
	BLACK	-0.0135	-0.2359	-0.1189	-0.1128			
	BW	0.1778	0.3605	0.1725	-0.0890	-0.1849		
	CHIL	0.1745	0.0958	0.0504	-0.1088	0.1525	0.0128	
	TOTINC	0.0656	0.1800	0.0370	0.1705	-0.1197	0.0560	-0.0708

a: Cities> 500,000, 2003 & 2005

b: All regions implies 4 regions listed

Source: 2003 and 2005 PSID

Table 3.4 reports the correlations. There appear to be no large differences between the regions, with the exception of a few variables. The variable TRUCK is correlated only about 18 percent with GASEXP in the Gulf Coast and Midwest, but is 27 percent correlated in the West Coast and over 33 percent correlated in the Central Atlantic.

Further, while COLGRAD is slightly positively correlated with GASEXP in the majority of regions, it is slightly negatively correlated with GASEXP in the Central Atlantic. BLACK is also largely uncorrelated with GASEXP in the majority of regions, but negatively correlated 15 percent in the Gulf Coast. CHIL also appear to have a negligible correlation with GASEXP in the Gulf Coast and Midwest, but these are correlated 10 percent in the Central Atlantic and 17 percent in the West Coast.

Also included is Table A.3 in the Appendix, which illustrates the percentage of yearly income devoted to gasoline expenses. The Central Atlantic clearly has the smallest proportion of income devoted to gasoline of any of the regions, followed by the West Coast. The Gulf Coast devotes the most income to gasoline. We would then expect the coefficient for income in the regression to be the largest in the Gulf Coast and the smallest for the Central Atlantic.

4. Results

4.1 State Results

I first present the state results to motivate how the price elasticity of gasoline demand varies throughout the country without controlling for city size. Looking at how the elasticity of gasoline demand varies across the United States as a whole helps support my key results, seen in the regional estimations.

I estimate Eq. (2) and obtain the predicted short-run price elasticities of gasoline demand for each state. They range from -1.278 to .639. Table A.4 in the Appendix provides the underlying regression results. The regression explains just over 10 percent of the variation in gasoline expenditures. Note that for some states the regression predicts positive elasticities; these are outliers for the most part, representing smaller sample sizes than the majority of states in the regression. Thus, not many of the positive elasticities are significantly different than zero.[4] Further, over 80 percent of the estimates are within a more reasonable range of -.604 to .087. The average estimate for all states, without controlling for size, is -.264.

The map shown in Figure 2 of the Appendix illustrates that while gasoline varies broadly throughout the United States, certain regions appear to have roughly similar gasoline demand. By region, it appears that the Gulf Coast/Southwest has the most inelastic demand for gasoline in the short run, followed by the Central Atlantic. The Midwest and the West Coast appear to be the most elastic. There appear to be no large overarching trends except for the central, southern portion of the country having the most inelastic gasoline demand.

4.2 Regional Results

The regional estimation was also run using gasoline price as the core explanatory variable. Other demographic variables, like income, two cars, truck, college, black, both spouses work, and number of children were then added. Solely using price with regional interaction terms resulted in just under 10 percent of the variation in gasoline expenditures being explained by the regression.[5] Demographic variables alone explained

[4] For instance, the standard error for the coefficient of lnP for Delaware is 1.30, more than twice the size of value predicted.

[5] The inclusion of income increased the explanatory power of the regression by .4%. The other demographic variables added individually with gasoline price and income explained less than an additional 1%, except for both spouses working, which explained roughly 2%. All variables individually had significance for at least one region, at the 5 percent level. The full regressions added slightly more explanatory power.

15.6% of the variation in gasoline expenditures, while the addition of variables for mass transit use explained 16.1%, the addition of a variable for the density of MSA explained 16.2%, and both mass transit use and density explained 16.3%.The inclusion of both urban form variables does not appear to increase the explanatory power of the estimation, only to decrease the effect of the individual urban form coefficients. All variables retained significant explanatory power for at least one region, except for the truck variable, which was found to be insignificant.

The key variables and their coefficients can be seen in Table 4.1.[6] Only the interaction terms with gasoline price are reported, as those are the ones important for determining the price elasticity of gasoline demand. The Midwest region is the excluded dummy; the additional coefficients for the other regions then follow. The signs of the interaction variable coefficients were roughly as expected.

Mass transit use, MTRANS and density, lnDEN both showed the expected negative effects on the price elasticity of gasoline demand. Income was also negative, but only resulted in significantly more elastic demand on the West Coast. Income was expected to have an ambiguous effect on gasoline demand. Having two cars, TWOCAR, was only negative in the Central Atlantic, actually increasing the inelasticity of gasoline demand in the rest of the country. The presence of two cars was predicted to reduce gasoline demand because one of the cars might have better fuel economy and gasoline consumption could have been reduced by switching vehicles. Further, the sign for having a truck, TRUCK, becomes ambiguous, as the variable has no significant effect on the price elasticity of gasoline. Having a truck was thought to reduce gasoline demand

[6] The regression was also run without regional dummies. The signs and magnitudes of the coefficients were roughly similar, but the regression explained less than 14 percent of the variation in gasoline expenditures (compared to over 16 percent with regional dummies).

because of the disproportionate effect of higher gasoline prices on truck gasoline expenditures. Much of TRUCK's effect could have been explained by TWOCAR, given their high correlation in all regions.

Table 4.1: Regressions for Price Elasticity Using Equation (2)[a], 2003-2005

Dependent Variable: lnGAS = ln(Gasoline Expenditures)										
	(1)	s.e.	(2)	s.e.	(3)	s.e.	(4)	s.e.	(5)	s.e.
lnP	1.463	(1.13)	1.408	(1.14)	3.008**	(1.28)	2.864**	(1.36)	2.498***	(0.52)
lnPlnI	-0.101	(0.11)	-0.080	(0.11)	-0.122	(0.11)	-0.104	(0.11)	-0.163***	(0.05)
lnP*MTRANS			-1.373	(0.88)			0.052	(1.12)		
lnP*lnDEN					-0.188***	(0.38)	-0.194**	(0.09)		
lnP*TWOCAR	0.344*	(0.18)	0.315*	(0.18)	0.343*	(0.18)	0.338*	(0.18)	0.154*	(0.09)
lnP*TRUCK	0.012	(0.15)	-0.005	(0.15)	-0.038	(0.15)	-0.033	(0.15)	-0.061	(0.07)
lnP*COLGRAD	-0.133	(0.16)	-0.114	(0.16)	-0.136	(0.16)	-0.148	(0.16)	-0.068	(0.08)
lnP*BLACK	0.008	(0.14)	0.012	(0.14)	-0.060	(0.14)	-0.051	(0.14)	-0.248***	(0.09)
lnP*BW	0.115	(0.17)	0.131	(0.17)	0.156	(0.17)	0.146	(0.17)	0.136*	(0.08)
lnP*CHIL	0.140***	(0.05)	0.144***	(0.05)	0.151***	(0.05)	0.147***	(0.05)	0.016	(0.02)
West*lnP	4.596**	(1.81)	5.093***	(1.84)	5.692***	(2.11)	5.721***	(2.16)	1.220	(0.93)
West*lnPlnI	-0.396**	(0.18)	-0.390**	(0.18)	-0.371**	(0.18)	-0.375**	(0.18)	-0.133	(0.09)
West*lnP*MTRANS			-5.372**	(2.58)			-4.503	(2.81)		
West*lnP*lnDEN					-0.210	(0.14)	-0.134	(0.16)		
West*lnP*TWOCAR	0.500*	(0.30)	0.504	(0.31)	0.494	(0.31)	0.483	(0.31)	0.049	(0.18)
West*lnP*TRUCK	-0.070	(0.24)	-0.130	(0.25)	-0.047	(0.25)	-0.102	(0.25)	0.340**	(0.14)
West*lnP*COLGRAD	0.323	(0.27)	0.357	(0.27)	0.355	(0.27)	0.354	(0.27)	-0.009	(0.16)
West*lnP*BLACK	0.024	(0.25)	0.113	(0.26)	0.315	(0.27)	0.323	(0.27)	0.338*	(0.19)
West*lnP*BW	-0.864***	(0.25)	-0.876***	(0.26)	-0.809***	(0.26)	-0.826***	(0.26)	-0.070	(0.14)
West*lnP*CHIL	-0.086	(0.08)	-0.104	(0.08)	-0.096	(0.08)	-0.107	(0.08)	-0.004	(0.05)
Gulf*lnP	0.849	(1.67)	1.193	(1.72)	dropped		dropped		-5.343***	(0.81)
Gulf*lnPlnI	-0.076	(0.16)	-0.116	(0.17)	-0.074	(0.17)	-0.092	(0.17)	0.492***	(0.08)
Gulf*lnP*MTRANS			dropped				dropped			
Gulf*lnP*lnDEN					0.112	(0.28)	0.141	(0.28)		
Gulf*lnP*TWOCAR	0.049	(0.29)	-0.008	(0.29)	-0.035	(0.29)	-0.030	(0.30)	-0.267*	(0.15)
Gulf*lnP*TRUCK	0.170	(0.25)	0.296	(0.26)	0.328	(0.26)	0.323	(0.26)	0.379***	(0.13)
Gulf*lnP*COLGRAD	-0.647**	(0.27)	-0.561**	(0.28)	-0.539*	(0.28)	-0.528*	(0.28)	-0.378***	(0.14)
Gulf*lnP*BLACK	0.572**	(0.24)	0.456*	(0.24)	0.528**	(0.24)	0.518**	(0.24)	0.594***	(0.13)
Gulf*lnP*BW	0.116	(0.27)	0.063	(0.28)	0.037	(0.29)	0.048	(0.28)	0.177	(0.13)
Gulf*lnP*CHIL	-0.299***	(0.08)	-0.292***	(0.08)	-0.300***	(0.08)	-0.296***	(0.08)	-0.047	(0.04)
CAtlantic*lnP	1.409	(2.31)	0.964	(2.53)	0.103	(2.74)	-0.530	(2.87)	-2.709***	(0.91)
CAtlantic*lnPlnI	-0.049	(0.22)	0.023	(0.24)	0.047	(0.24)	0.052	(0.24)	0.290***	(0.09)
CAtlantic*lnP*MTRANS			0.088	(1.24)			-1.342	(1.66)		
CAtlantic*lnP*lnDEN					0.041	(0.16)	0.193	(0.22)		
CAtlantic*lnP*TWOCAR	-0.647**	(0.28)	-1.078***	(0.30)	-1.069***	(0.30)	-1.102***	(0.30)	-0.664***	(0.16)
CAtlantic*lnP*TRUCK	-0.384	(0.29)	-0.136	(0.32)	-0.081	(0.32)	-0.111	(0.32)	0.055	(0.14)
CAtlantic*lnP*COLGRAD	0.619*	(0.32)	0.829**	(0.36)	0.828**	(0.36)	0.857**	(0.36)	0.310**	(0.14)
CAtlantic*lnP*BLACK	-0.421	(0.26)	-0.393	(0.33)	-0.136	(0.30)	-0.332	(0.35)	0.150	(0.14)
CAtlantic*lnP*BW	-0.782***	(0.29)	-1.049***	(0.32)	-1.099***	(0.33)	-1.069***	(0.33)	-0.128	(0.14)
CAtlantic*lnP*CHIL	-0.053	(0.10)	0.058	(0.12)	0.045	(0.12)	0.054	(0.12)	0.010	(0.05)
Obs.	6974		6553		6553		6553		25730	
Households	3943		3691		3691		3691		13648	
R^2	0.156		0.161		0.162		0.163		0.159	

a: MidWest was the excluded dummy; All regressions except (5) on cities > 500,000
(1) Specification 1 includes all demographic variables
(2),(3),(4) Specification 2 adds mass transit data, while 3 adds density data, 4 includes both
(5) Specification 5 is specification 1, but on cities of all sizes
*** Signfies significance at 1% level, ** at 5%, and * at 10%
Standard errors in parentheses

For more demographic variables, graduating college, COLGRAD, had a significant negative impact on the price elasticity of gasoline demand in all regions, as predicted. Whether the head of household was black or not, BLACK, was only significant in the Gulf Coast, where it led to more inelastic demand as expected. It might not have been significant in other regions because of smaller minority populations; the Gulf Coast had the largest proportion of respondents classifying themselves as black. Whether both the head of the household and their spouse worked or not, BW was highly significant, but only in the West Coast and Central Atlantic regions. The West Coast and Central Atlantic have slightly higher proportions of BW, but the difference is not much more than 5 percent. The sign was also negative, making gasoline demand more elastic for BW, which was the opposite of what was expected. The variable for number of children, CHIL, was only significant for the Gulf Coast and Midwest. The signs for the variable, however, were negative in the Midwest and positive in the Gulf Coast, leading the effect to be ambiguous for the price elasticity of the country as a whole. A higher number of children was thought to make gasoline demand more inelastic.

4.3 Predicted Regional Price Elasticities

To determine the short-run price elasticity of gasoline demand, on average, for cities in a region, I use the coefficients of lnP and its interaction terms along with regional values for the demographic variables, region, use of mass transit, and the density of the city. The price elasticity determined is then for gasoline expenditures; the results listed have been modified to reflect the price elasticity for gallons of gasoline consumed.[7] I estimate four elasticities for each region; the corresponding regressions are in Table 4.1. The first elasticity was obtained using only demographic variables (1), the second adding mass transit (2), the third adding density (3), and the fourth adding both mass transit and density (4). Table 4.2 provides the results.[8] The four different regressions all produced roughly similar results. Unsurprisingly, the Central Atlantic region, which has the highest density and most mass transit use, produced the most elastic gasoline demand. The Midwest had the most inelastic gasoline demand, even though it contained the second densest cities and second most mass transit use. The Midwest did have the lowest average household income of any region though, over $17,000 less than either the West Coast or Central Atlantic, which would have made gasoline demand more inelastic. The Gulf Coast is also surprising; as it was the second most elastic region, even though it had the lowest density, lowest mass transit use, and second lowest income. Further the Gulf Coast had the largest proportion of income devoted to gasoline expenditures, making it seemingly more susceptible to price shocks.

Table 4.2: Price Elasticities Predicted by Equation (2)[a]

	Regression	(1)	(2)	(3)	(4)	Average
Area From	West Coast	-0.252**	-0.239**	-0.320**	-0.304**	-0.279
	Gulf Coast	-0.309	-0.345	-0.346***	-0.347***	-0.337
	Midwest	-0.212***	-0.197***	-0.285***	-0.278***	-0.243
	C. Atlantic	-0.381	-0.350	-0.432	-0.348	-0.378

a: Cities >500,000, Years 2003 & 2005
(1) Specification 1 includes all demographic variables; corresponding to Reg (1) from Table 4.1
(2),(3),(4) Specification 2 adds mass transit data, while 3 adds density data, 4 includes both; they correspond to Reg (2), (3), and (4) from Table 4.1
*** Signfies significance at 1% level, ** at 5%, and * at 10%

[7] The results from the regression were reduced by 1 to put them in a form similar to the literature. Initially my regression captured $\%\Delta GasExp = \beta*\%\Delta P$ (4), which is similar to $\%\Delta P + \%\Delta Gal = \beta_1*\%\Delta P$. I want to determine β_2 for $\%\Delta Gal = \beta_2*\%\Delta P$ (5). (4) then, is also equivalent to $\%\Delta Gal = (\beta_1-1)*\%\Delta P$.
[8] When run without regional dummies, the predicted elasticities were similar. The Central Atlantic was still the most elastic, while the Gulf Coast was the most inelastic.

An F-test determined that the estimates obtained were on the whole significantly different from zero. All estimates obtained for the West Coast were significant at the 5 percent level, with those of the Midwest significant at the 1 percent level. Estimations made for the Gulf Coast were significant at the 1 percent level using the density and demographic regression (3) and using the mass transit, density, and demographic regression (4). Surprisingly, none of the estimations for the Central Atlantic were significantly different from zero, even at the 10 percent level, despite the fact that the Central Atlantic had the largest predicted price elasticity.

Table 4.3: Price Elasticities Found by Altering Mass Transit and Density

Regression Used	Change From Current	-20%	-10%	0%	10%	20%	30%	Difference	% Variation[a]
(2) Reg 1 w/ mass transit	West Coast	-0.100	-0.169	-0.239	-0.309	-0.379	-0.449	-0.349	**350.6%**
	Gulf Coast	-0.333	-0.339	-0.345	-0.352	-0.358	-0.364	-0.032	**9.5%**
	Midwest	-0.166	-0.181	-0.197	-0.212	-0.228	-0.243	-0.077	**46.6%**
	C. Atlantic	-0.259	-0.304	-0.348	-0.393	-0.437	-0.482	-0.222	**85.8%**
(3) Reg 1 w/ density	West Coast	-0.231	-0.278	-0.320	-0.358	-0.392	-0.424	-0.193	**83.6%**
	Gulf Coast	-0.329	-0.338	-0.346	-0.353	-0.360	-0.366	-0.037	**11.2%**
	Midwest	-0.243	-0.265	-0.285	-0.303	-0.319	-0.334	-0.091	**37.6%**
	C. Atlantic	-0.399	-0.416	-0.432	-0.446	-0.458	-0.470	-0.071	**17.9%**

a: Total change in use of mass transit or density was 62.5%

Price elasticity determined by increasing or decreasing use of mass transit and city density

Original regressions found in Table 4.1

Cities >500,000, Years 2003 & 2005

The urban form of each region was then altered by a percentage from its current level in order to illustrate how improved urban form might affect each region.[9] The results can be seen in Table 4.3. Only in the West Coast were the variations in price elasticity greater than the changes made to both usage of mass transit and city density.[10] The other regions largely had muted effects. For example, the estimation predicts that for every 10 percent increase in city density, the Midwest will only experience a 6 percent

[9] This was accomplished by altering the mass transit value used with the coefficient lnP*MTRANS or by altering the city density value used with lnP*lnDEN.

[10] The Central Atlantic did experience changes for mass transit, but was inelastic to changes in city density.

increase in the price elasticity of gasoline demand. With the exception of the West Coast, the regions are all relatively insensitive to any changes in either mass transit or density in the short run. This further supports the hypothesis that personal preferences are more important in the short run and that behavior is sticky in the short run.

5. Conclusion

The state estimations of the short-run price elasticity of gasoline demand provide evidence of regional variation in the elasticity of gasoline demand for the United States as a whole. The regional estimations further support that the price elasticity of gasoline demand varies at the city level. Further, the majority of regions appear insensitive to changes in either density or mass transit in the short run. This casts doubt as to whether changes in urban form can lead to changes in gasoline demand. Further, because the regional regressions only explain about 16 percent of the variation in gasoline expenditures, much of the extra variation might come from personal preferences that cannot be captured in my regressions. People in regions like the Midwest might derive more utility from driving than those in the Central Atlantic or West Coast regions. This could stem from moving to a particular area because of an interest in driving. More likely though, when people grew up in a particular region they came to see a car as a necessity. I find that changes in the urban form of cities would result in only small changes in the short-run elasticity of gasoline demand. Policy makers will most likely have to work through methods such as increased gasoline taxes in order to truly curb gasoline demand.

In the future it might be interesting to look at changes in urban form in the long-run. In the short-run people might choose to pay more for gasoline in the hopes that the price will decline in the near future. Even if they have readily available alternatives to driving, such as mass transit, they might view this as too burdensome a change for the benefit. In the long-run people will be more likely to make changes since any changes in gasoline prices will be more permanent. People will then likely value living in denser regions, better served by mass transit. Nevertheless, they would also have other options which were not possible in the short-run, such as replacing their vehicle with one that is more fuel efficient. Such long-run questions need to be explored before urban form is completely discounted as a way of reducing gasoline demand.

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Appendix

Table A.1: Variables and Data Sources

Type	Variable	Description and Source
Location Based	P	Gasoline price in the previous month, adjusted for inflation to year 2000. Source: Energy Information Administration
	MTRANS	% of population in a particular city using public transportation (excluding taxis). Source: US Census
	DEN	Population per square mile in Metropolitian Statistica Areas (MSA). Source: US Census
Household Based	GAS	Gasoline expenditures in the previous month. Source: PSID Interviews
	TOTINC	Total taxable income in the previous year. Source: PSID interviews
	TWOCAR	Dummy variable, 1 if the household had two are more cars when interviewed. Source: PSID interviews
	TRUCK	Dummy variable, 1 if the household had a truck in their vehicle stock when interviewed. Source: PSID interviews
	COLGRAD	Dummy variable, 1 if the head of household had a college degree at the time of the interview. Source: PSID interviews
	BLACK	Dummy variable, 1 if the head of household was black. Source: PSID interviews
	BW	Dummy variable, 1 if both the head of the household and their spouse worked. Source: PSID interviews
	CHIL	Number of children present in the household 17 or younger at the time of interview. Source: PSID interviews

Table A.2: States In Each Region

West Coast	Gulf Coast	Midwest	Central Atlantic
Arizona	Alabama[a]	Illinois	Delaware[a]
California	Arkansas[a]	Indiana	District of Columbia
Nevada*	Louisiana	Iowa[a]	Maryland
Oregon	Mississippi[a]	Kansas[a]	New Jersey
Washington	New Mexico[a]	Kentucky[a]	New York
	Texas	Michigan	Pennsylvania
		Minnesota	
		Missouri	
		Nebraska[a]	
		North Dakota[a]	
		Ohio	
		Oklahoma[a]	
		South Dakota[a]	
		Tennessee[a]	
		Wisconsin	

a: States with too few observations to be considered in city regressions

Source: 2003 and 2005 PSID

Table A.3: Gasoline Expenses as % of Total Income[a]

		% of Income[b]
Region	C. Atlantic	3.59%
	Midwest	4.95%
	Gulf Coast	5.43%
	West Coast	4.10%
State	Arizona	4.53%
	California	4.05%
	Colorado	3.24%
	Connecticut	1.30%
	DC	3.53%
	Florida	4.83%
	Illinois	4.34%
	Indiana	4.95%
	Kansas	4.76%
	Louisiana	8.50%
	Maryland	3.70%
	Massachusetts	2.22%
	Michigan	6.53%
	Minnesota	3.36%
	Missouri	5.16%
	New Jersey	2.54%
	New York	2.73%
	Ohio	4.84%
	Oregon	5.64%
	Pennsylvania	6.56%
	Texas	5.16%
	Virginia	4.94%
	Washington	3.49%
	Wisconsin	4.40%

a: Years 2003, 2005

b: Monthly gasoline expenditures adjusted for yearly consumption, for cities >500,000

Source: 2003 and 2005 PSID

Table A.4: Price Elascity by State Using Eq (2)[a]

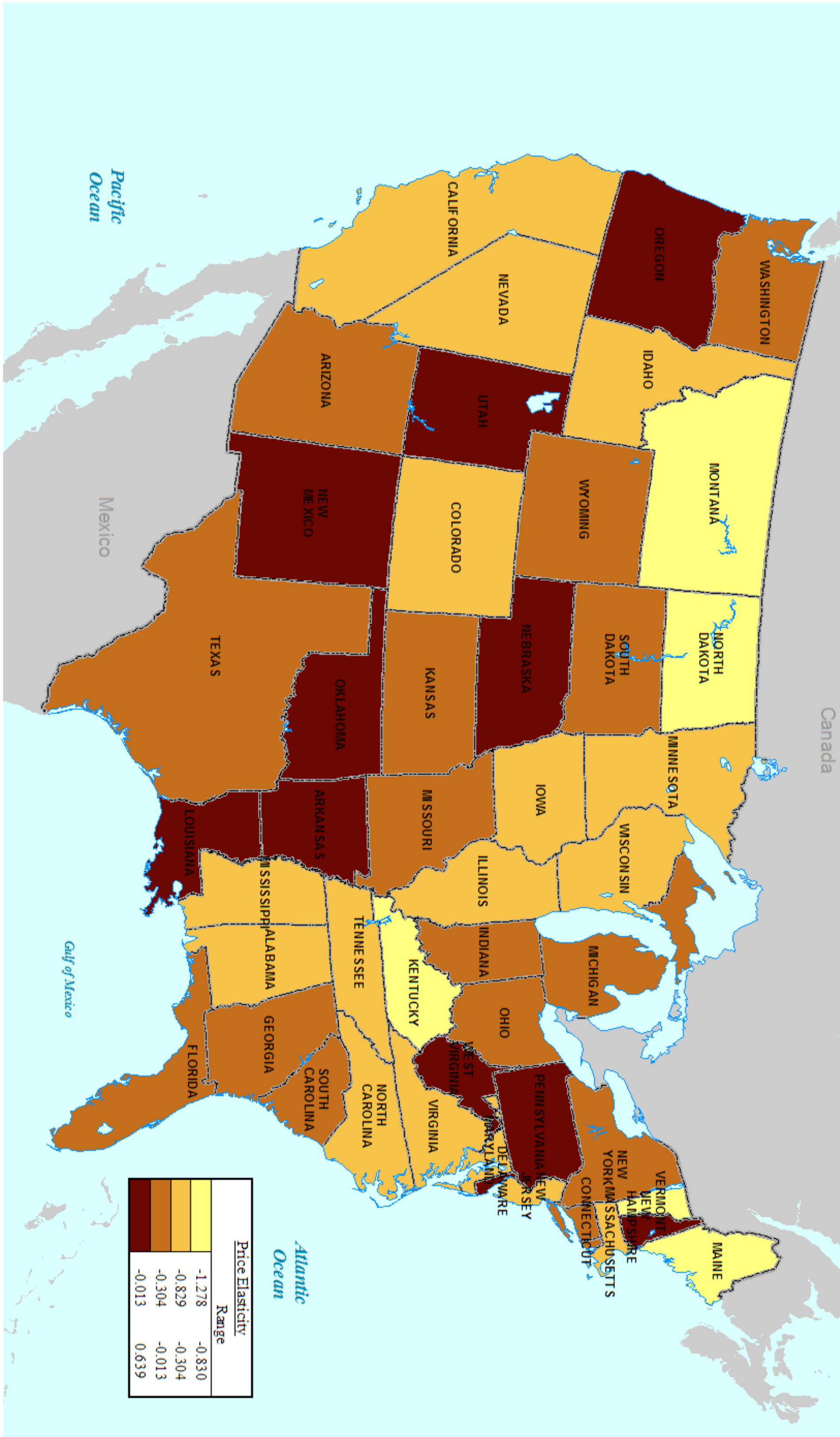
Dependent Variable: lnGAS = ln(Gasoline Expenditures)					
State	Value of lnP	S.E.	Value of lnPlnI	S.E.	Implied Price Elasticity
NY[b]	0.806***	(0.28)	0.016	(0.02)	-0.065
AL	-0.729***	(0.22)	0.0479***	(0.01)	-0.434
AZ	-0.043	(0.22)	-0.004	(0.01)	-0.141
AR	-0.026	(0.17)	0.0215***	(0.01)	0.070
CA	-0.378***	(0.13)	0.0101**	(0.00)	-0.366
CO	-0.309	(0.19)	0.004	(0.01)	-0.347
CT	-0.422	(0.37)	0.0571***	(0.02)	-0.013
DE	0.622	(1.30)	-0.040	(0.07)	0.227
DC	-0.407	(0.39)	0.000	(0.02)	-0.483
FL	-0.472***	(0.14)	0.0322***	(0.01)	-0.286
GA	-0.066	(0.15)	-0.003	(0.01)	-0.162
ID	-0.244	(0.47)	-0.011	(0.02)	-0.401
IL	-0.633***	(0.16)	0.0233***	(0.01)	-0.510
IN	-0.393**	(0.16)	0.0369***	(0.01)	-0.168
IA	-0.443**	(0.18)	0.0210***	(0.01)	-0.342
KS	-0.338	(0.28)	0.0408***	(0.01)	-0.086
KY	-0.934***	(0.20)	0.0215***	(0.01)	-0.830
LA	0.788***	(0.19)	-0.010	(0.01)	0.639
ME	-1.173***	(0.44)	0.0407**	(0.02)	-0.885
MD	-0.444***	(0.16)	0.003	(0.01)	-0.477
MA	-0.678***	(0.21)	0.0493***	(0.01)	-0.332
MI	-0.195	(0.14)	0.008	(0.01)	-0.200
MN	-0.429**	(0.19)	0.006	(0.01)	-0.439
MS	-0.539***	(0.15)	0.0313***	(0.01)	-0.376
MO	-0.627***	(0.17)	0.0519***	(0.01)	-0.277
MT	-1.305**	(0.54)	0.011	(0.03)	-1.278
NE	0.274	(0.22)	-0.0220***	(0.01)	0.033
NV	-0.805***	(0.28)	0.0421***	(0.01)	-0.523
NH	-0.226	(0.43)	0.0422***	(0.01)	0.031
NJ	-0.656***	(0.18)	0.0429***	(0.01)	-0.350
NM	0.519	(0.49)	-0.023	(0.03)	0.264
NC	-0.526***	(0.14)	0.0121**	(0.01)	-0.496
ND	-0.462	(0.95)	-0.048	(0.05)	-0.925
OH	-0.091	(0.14)	0.0170***	(0.01)	-0.021
OK	0.573**	(0.27)	-0.001	(0.01)	0.502
OR	0.007	(0.22)	0.0142**	(0.01)	0.050
PA	0.102	(0.15)	0.003	(0.01)	0.054
RI	-0.766	(0.78)	0.0765**	(0.03)	-0.192
SC	-0.088	(0.14)	0.005	(0.01)	-0.123
SD	-0.447	(0.38)	0.0318**	(0.02)	-0.266
TN	-0.539***	(0.19)	0.0384***	(0.01)	-0.304
TX	-0.377***	(0.14)	0.0242***	(0.01)	-0.252
UT	-0.186	(0.22)	0.0388***	(0.01)	0.064
VT	-1.048	(0.82)	-0.009	(0.03)	-1.191
VA	-0.821***	(0.15)	0.0351***	(0.01)	-0.604
WA	-0.132	(0.20)	0.010	(0.01)	-0.114
WV	0.251	(0.57)	-0.012	(0.03)	0.087
WI	-0.433**	(0.19)	0.007	(0.01)	-0.441
WY	-0.465	(0.75)	0.040	(0.04)	-0.258

a: Single regression shown in 2 columns

b: NY was the excluded dummy

Standard errors in parentheses

*** Signfies significance at 1% level, ** at 5%, and * at 10%


Pacific Ocean
Atlantic Ocean
Gulf of Mexico
Canada
Mexico
WASHINGTON
OREGON
CALIFORNIA
NEVADA
IDAHO
MONTANA
WYOMING
UTAH
ARIZONA
COLORADO
NEW MEXICO
NORTH DAKOTA
SOUTH DAKOTA
NEBRASKA
KANSAS
OKLAHOMA
TEXAS
MINNESOTA
IOWA
MISSOURI
ARKANSAS
LOUISIANA
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ILLINOIS
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INDIANA
OHIO
KENTUCKY
TENNESSEE
MISSISSIPPI
ALABAMA
GEORGIA
FLORIDA
SOUTH CAROLINA
NORTH CAROLINA
VIRGINIA
WEST VIRGINIA
MARYLAND
DELAWARE
PENNSYLVANIA
NEW JERSEY
NEW YORK
CONNECTICUT
MASSACHUSETTS
VERMONT
NEW HAMPSHIRE
MAINE
Price Elasticity
Range
-1.278 -0.830
-0.829 -0.304
-0.304 -0.013
-0.013 0.639