Does the Quality of Public Transit Affect Commuters' Response to Gasoline Price Changes?

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Abstract

The effect of public transportation on commuters' sensitivity to gas prices is examined using a proxy for the quality of public transportation. This proxy is measured as the difference in the individual's predicted commute times by private transit and public transit, estimated using the individual's observable characteristics. The interaction of gasoline price with this measure is found to have a significant effect on annual vehicle miles traveled. Further, there is a strong correlation between the quality of public transit and elasticity of demand. This indicates that public transit could play an important role in increasing the effectiveness of gasoline taxes. This has timely policy implications with regard to the federal allocations for public transit infrastructure in the 2009 stimulus bill.

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I. Introduction

The American Recovery and Reinvestment Act (ARRA), commonly referred to as the stimulus bill, was passed by Congress on February 13, 2009, and signed into law by President Obama on February 17. The $787 billion bill provides supplemental appropriations to areas especially hurt by the economic crisis and areas expected to help promote economic recovery. Among these allotments is $49.3 billion for transportation infrastructure, including $8.4 billion specifically for public transit and rail (GovTrack.us, 2009). Its possible uses include new construction, modernization of existing systems, and improvements to intermodal and transit facilities.

Despite the consensus on the urgent need for action evidenced by its quick passage through Congress, specific provisions of the ARRA were contested, including the infrastructure funding. Supporters promote infrastructure spending for its more lasting impact on the economy. They contend that the economy is likely to face a long downturn, a hypothesis supported by Federal Reserve Chairman Ben Bernanke's recent statements, and so dismiss the common critique that infrastructure spending is too slow in implementation. The bill also contains provisions to ensure the money is spent quickly, helping to address this concern. Opponents also cite the ability of political pressures to direct the spending, funding wasteful and unnecessary projects, as a reason to be skeptical of its utility (Associated Press, 2008 [2]).

The specific appropriation for public transit projects seeks to provide alternative forms of travel instead of simply improving and expanding the existing road system. Such a policy complements the desire to reduce the negative externalities associated with driving, such as harmful emissions, traffic fatalities, households' gasoline expenditures, and national security issues arising from the importation of oil. Importantly, public transit could play a role in altering drivers' sensitivity to gas prices by providing them with viable alternatives to driving. This possible role is notable because of the findings of the National Household Transport Survey (NHTS) that the number of household vehicles increased 23% from 1990 to 2001 and household vehicle miles traveled increased 34%. These trends highlight the potential difficulties associated with reducing gasoline consumption (Hu and Reuscher, 2004). Further, households spend about 2% of their income on this one commodity, making the fluctuation of gasoline prices a salient topic (West and Williams, 2007). This is especially true after the dramatic price fluctuations seen in 2008. Such concerns further motivate a reduction of gasoline consumption. The availability of quality public transit systems could be an effective method to facilitate a decrease in gasoline usage. This desire to reduce consumption and increase public awareness of price motivates this topic.

The impact of higher gas prices has been studied by evaluating changes in consumption and the subsequent price elasticity of demand, fleet composition, and negative externalities. However, to the best of my knowledge, the availability of public transit has not been expressly used as a determinant of the elasticity of demand for gasoline. In addition, the existing studies have focused on the state or national level, obscuring what could be more localized differences due to varying urban structure and public transportation systems. The purpose of this paper is to build upon the existing studies by incorporating a measure of the quality of public transit in a metropolitan area. The proxy is the difference in predicted commute time by private vehicle and predicted commute time by public transit. Individuals facing a lower time trade-off are expected to be more willing to switch modes. Cities with superior infrastructure allow more similar times and thus are expected to have more elastic demands for gasoline. Findings of differences in elasticities corresponding to the quality of the local public transportation system could have policy implications for the best allocation of infrastructure spending to maximize its potential benefits.

The paper is organized into the following sections. Section 2 presents a review of the existing literature on the impacts of changes in fuel prices. Section 3 presents the theoretical framework of my analysis. This is followed by a discussion of the data in Section 4. Section 5 presents the empirical methodology used in the analysis and discusses the regression results. Section 6 discusses the calculation of demand elasticities and further analyzes the implications of the results. Lastly, section 7 concludes.

II. Existing Literature

Gas prices have been studied through their impact on fleet composition (including age, type, and fuel efficiency of vehicles), vehicle miles traveled, number and type of vehicles owned by a household, and estimated emissions reductions. Given the similarities in dependent variables of interest, the literature differs in the independent variables found to be relevant to the analysis and the way some of these variables are formulated. For example, a variety of classifications have been used to describe vehicle size, type, and age (as a proxy for fuel efficiency) and heterogeneity of preferences within two-adult households. Bento, Goulder, Henry, Jacobsen, and von Haefen (2005) contributed to the literature by addressing market interactions for new, used, and scrapped cars and allowing for heterogeneity in household preferences. Fullerton and Gan (2005) employ these variables in a model of the effect of a gas tax on miles driven, type of vehicle chosen, and number of vehicles owned. They also estimate how price changes affect emissions and consumer surplus (from driving fewer miles and driving a less preferable type of vehicle). As a further advance, Feng, Fullerton, and Gan (2005) used a model that allowed the household's choice of the number of vehicles, type of vehicles, and miles traveled per vehicle to be made simultaneously and separately for each household member (for the latter two). The reduction in total emissions from the changes in these decisions was estimated as 0.136% for every 1% increase in price.

Many empirical studies also use these changes in the price of gas to measure elasticity of demand and changes in driving behavior. Some studies have estimated both short- and long-term elasticities, even if their data is from a relatively short time frame. Haughton and Sarkar (1996) provide perhaps the best example of a comprehensive analysis with their utilization of twenty-one years' worth of data in order to report long-run elasticities and estimate long term effects of rises in gasoline prices on consumption and vehicle miles traveled. They extend their analysis to model a $1 increase in gas prices due to an increased gas tax, providing even further evidence of the impact of gasoline price on consumption.

Studies consistently find a negative relationship between gas price and consumption. Haughton and Sarkar (1996) find own-price elasticities of demand for gasoline of -0.12 and -0.17 in the short run and -0.23 and -0.35 in the long run. They estimate that a $1 gasoline tax passed through fully to consumers would decrease consumption by 15-20% and miles driven by 11-12% while producing revenue of almost $100 billion annually. Bento et al. (2005) calculate the short-run elasticity of demand for gas consumption at about -0.27. West and Williams (2007) estimate the elasticity as -0.75 for one-adult households and -0.27 for two-adult households. This is roughly consistent with Sipes and Mendelsohn's (2001) earlier work that estimated short run elasticities of -0.4 to -0.6 and -0.5 to -0.7 in the long run. Table 1 provides a comparison of the short-run and long-run elasticities found in these studies. This analysis seeks to build on these models of gasoline consumption by introducing a variable for the availability of public transit as an alternate choice for travel. The availability is measured by the difference in commute times by private transit and public transit.

Table 1: Price Elasticity of Demand for Gasoline in Literature

Study	Short-Run	Long-Run
Dahl (1978)	-0.442	
Haughton and Sarkar (1996)	-0.12 to -0.17	-0.23
Sipes and Mendelsohn (2001)	-0.4 to -0.5	-0.7
Bento et al. (2005)	-0.27	
West and Williams (2005)	one-adult: -0.74 two-adult: -0.51	
West and Williams (2007)	one-adult: -0.75 two-adult: -0.27	

The impact of higher gasoline prices on fleet composition has also been analyzed. Feng et al. (2005) estimate that a 1% increase in the price of gas decreases the probability that a two-car household has one car and one SUV by 0.793% while increasing the probability of having two cars by 0.695%. Fullerton and Gan (2005) found figures of the same magnitude (with rounding). However, Bento et al. (2005) found that more than 95% of the reduction in gasoline consumption induced by a price increase was due to decreases in miles driven, rather than the alteration of the fleet composition to more fuel-efficient cars. Greg Mankiw (2006), in a *Wall Street Journal* opinion column, presents the numerous reasons why an increase in gas taxes should be implemented, including the impetus for motorists to drive less. He contends this could occur through motorists choosing to live closer to their workplace or take public transportation. This piece of his argument, along with Bento et al.'s (2005) finding that the majority of the decrease in consumption comes from reductions in miles traveled, illustrates the potential significance of the area in which I focus my analysis.

An additional segment of the literature has utilized these findings to analyze the extent of these changes on driving behavior. Decreases in consumption have obvious beneficial impacts because of the negative externalities associated with consumption. Economists have analyzed the efficiency and efficacy of inducing an increase in gas prices through an increase in the federal gasoline tax. Mankiw (2006) declares that the majority of economists agree that such a gas tax would be a more preferable policy tool than raising CAFE (Federal Corporate Average Fuel Economy) standards. Research has been conducted on the optimal level of a gas tax. West and Williams (2007) estimate the optimal tax rate as between \$.75 and \$1.30, depending on a one-adult or two-adult household and assumptions of homotheticity for utility and separability of leisure in the utility function. Other studies have attempted to quantify the marginal costs and benefits of a tax (Fullerton and Gan, 2005, Bento et al., 2005, for example) and the environmental costs and benefits of the reduction in emissions (Sipes and Mendelsohn, 2001, Stern, 2006). These studies have recovered consistent ranges for price elasticities and for the positive impact of higher prices; however, they have not allowed for the possibility that local differences in public transit may impact these effects and therefore alter the extent of the impacts in different areas.

A smaller body of literature has examined the interaction between transit prices and demand for public transportation, given the common existence of public transit even in small urban areas. Su and DeSalvo (2008) examine the effects of transport subsidies on the spatial size of a metropolitan area by theorizing that residents will choose the mode, either public or private (assumed to be an automobile), that has a lower cost. The marginal cost of public transit is assumed to be mainly a time cost, since behavior studies have shown that waiting for the transit vehicle to arrive is more onerous to travelers than being stuck in traffic in a private vehicle. Increases in the price of automobile travel relative to public transit cause a substitution towards public transit. Su and DeSalvo find that this should increase the area (modeled as a certain distance from the city center, defined as the primary business center) over which residents will choose to utilize public transit, thus increasing overall usage. Their analysis focuses on the effect of transportation subsidies on urban sprawl, and they model the effect of urban-area land size as a function of demographics, transit costs to passengers, and government transit expenditures. They employ the assumption that individuals living closer to the city center are more likely to use public transit, and therefore a larger urban radius increases the use of public transit. My analysis builds on this finding of substitution due to relative price changes by formally examining elasticities of demand specific to areas with different qualities of public transit. This directly models the trade-off and its effects on personal gasoline consumption rather than the examination of the effects on urban area done by Su and DeSalvo. More anecdotal evidence of the substitution effect is provided by a November 4, 2008 news release by the NPD Group, a market research firm, which found that 6.5% of surveyed consumers have responded to the higher fuel prices faced in 2008 by using public transit.

Grazi, van den Bergh, and van Ommeren (2008) find a similar relationship between urban form and transportation choices. Greater urban density decreases the probability of using a car and is related to a shorter commuting distance. In more densely populated areas, workers shift to other forms of travel besides an automobile because the time-cost of public transit is “substantially reduced” (Grazi et al., 2008, p. 109). This is due to a better public transit network and frequency of service in addition to the greater driving time because of the congestion that comes with high density areas. They also cite the costs of parking in these high-density areas as a motivation for the modal shift.

Zhou, Kim, Schonfeld, and Kim (2008) model the elasticity of demand for public bus service as a function of the potential demand density of the service times a quantity involving the wait time, average access time, average in-vehicle time, and fare price multiplied by factors that account for the elasticity of each component of this quantity. While this demand is forecasted in order to evaluate the impact of subsidies on bus transit systems, numerical results on the costs of a bus system and the optimal design of such a system to maximize welfare could prove helpful for metropolitan areas seeking to reduce the amount of automobile travel. Further, their model affirms Su and DeSalvo's (2008) conclusion that the largest component in weighing the decision between public transit and automobile travel is the time cost associated with each instead of just a direct monetary cost comparison.

Another important consideration in examining residents' response to increases in gasoline prices is their knowledge of their alternatives to traveling by private vehicle. A recent study of inner-city residents in Stockholm found that residents in general had good knowledge of public transportation, although they had less knowledge along lesser-known transit corridors (Dziekan, 2008). This knowledge was not affected by demographic variables that generally affect the use of public transit, such as age, employment, education, and automobile availability. It is also found that, although frequent users had more detailed knowledge of the system, less-frequent users were not substantially less knowledgeable (Dziekan, 2008). With signage of stops and the visibility of transit vehicles on main corridors, there is no reason to assume that this finding would not also hold in metropolitan areas in the United States.

III. Theoretical Framework

Driving is an integral part of the modern lifestyle and workweek, evidenced by the fact that 87.9% of the United States population commuted to work in a car and of these, 75.7% drove alone, according to the 2000 Census (Reschovsky, 2004). In the short run, these trips cannot be eliminated from a household's daily miles traveled in order to avoid higher gas prices nor can they be immediately altered in distance. Because of this, the means by which workers can most quickly, easily, or cheaply get to work could have a significant effect on the demand for gas. If consumers can choose alternate means, in this case public transit, a metropolitan area with superior transportation options will have a more elastic demand for gasoline than the national average. This reflects individuals' ability and willingness to switch to alternate modes rather than absorb the increased costs of continuing to travel solely by automobile. Furthermore, such commuting trips may be easier to switch than other vital household trips, such as shopping for groceries and driving children to activities. This, in addition to the regularity of commuting, motivates its use as the type of trip utilized in this analysis.

Households, as with all economic decisions, will choose their miles traveled and the manner in which they travel them (public transit and automobile travel are modeled as two numeraire goods in this context) to maximize their utility. Parry and Small (2008) contend that this utility is affected by the total cost of travel, which includes components such as service frequency, speed, wait time at transit stops, the externalities of pollution and accidents inflicted by other drivers, and direct monetary costs. In most situations, travel by public transit should be expected to take longer because of the wait time for the transit vehicle to arrive, slower speed of travel of the vehicle, and the number of stops made en route. Individuals therefore not only compare the difference in monetary costs, such as the fare price versus gasoline and possibly parking costs, but also consider the time and hassle associated with the trip.

Metropolitan areas within the United States differ in their provision of public transportation. These differences are seen in the modes of transportation offered, route density, and route frequency. The availability of this alternate form of travel, its relative cost, and its ease of use should affect the public's choice to adopt this as a mode of personal transport. The possibility of switching modes without significant sacrifices of time or convenience, which pose a more significant deterrent to using public transportation than fare prices, makes these two goods more substitutable. Therefore, metropolitan areas with more substitutable modes of transport due to the differences mentioned above should see more workers switching away from automobiles in times of high gasoline prices, making these areas characterized by higher elasticities.

According to Su and DeSalvo (2008), those living closer to the central business district (or city center) are assumed to generally use public transit more than other citizens. This represents an example of non-random sorting or self-selection if workers have chosen their residential or office locations based on concerns about the ease of commuting or cost-of-living concerns that include travel costs. Since this consideration already has entered their more permanent selection of residence or workplace, they may be less likely to alter their daily consumption and method of transportation based on such price or time concerns. Grazi et al. (2008) note that workers chose their residential location, conditional on their workplace location, by evaluating a trade-off between commuting cost and housing price. Therefore, there may be a relationship between density of their residential area and their preferred mode of commute, with those near the denser business districts choosing to pay higher housing prices in order to have a shorter commute with greater possible modes of commute.

However, Grazi et al. (2008) further report that the literature on such sorting (including other factors such as preferred lifestyle, security concerns, and access to educational and recreational facilities) is debated in transport economics, not just in the extent to which it occurs but also whether it occurs at all. After their own analysis of commuting distance, they find that endogeniety problems with urban density are small, and they believe that their OLS estimations are therefore accurate. They find more of a problem when analyzing choice of travel mode and therefore prefer their IV estimations.

In an effort to address the possibility of a selection problem, I compare people with similar demographic characteristics, making the assumption that individuals who are similar in observable characteristics will tend to locate in similar areas of the city. For example, Matthews (2007) notes an impact of street layout on house values. More pedestrian- or automobile-friendly areas, with differing levels of connectivity, are expected to differ in property values, so matching people based on income would take into account some of these selection factors. This also addresses Grazi et al.'s (2008) findings of a willingness to pay more for proximity to the city center. Similarly, Glaeser, Gyourko, and Saks (2006) find that increases in productivity raise both wages and housing prices. While they are analyzing the housing market and specifically differences in housing supply, the increase in both of these factors lends further credence to the assumption that observable factors such as income relate to housing prices and thus the area in which an individual chooses to locate since areas differ in average home values. Furthermore, spatial differences, such as unit-density of the residential area and proximity to the urban core (evaluated by residents as less attractive neighborhoods) impact the level of prices and predictions of prices and future appreciation (Glaeser and Gyourko, 2007). These observables will therefore control for location decisions because these decisions will be more similar among those of matching demographic characteristics.

In effect, I am using observable characteristics as a proxy for neighborhood location to account for this possible sorting. If this assumption holds, then the selection bias will not be a concern. The specifics of this procedure are discussed further in the methodology section. A more precise method to address the possible sorting bias is unavailable without more specific tract-level data from the NHTS and tract-level location identifiers from the Census. Such data would require security clearance to access, a process that is not an option due to the time constraints of this study. The other way to address this problem would be to roughly match the NHTS individuals to their Census tract based on the population density of the tract. Tract density is reported for each individual in the NHTS and can be created for each Census tract from Census data. This latter measure requires the attribution of an equal population density to each tract within the Census PUMA (Public Use Microdata Area), which is the smallest geographic unit at which individual data from the Census are publicly available. Densities are not available at the tract-level due to confidentiality concerns, and so the total PUMA density would have to be equally distributed to each tract within the PUMA as a best estimate. This procedure is also not undertaken because of time constraints.

Another consideration is the possible difference among those individuals willing to make the switch to public transit for their commute and those who are not. Certain people who use public transit for other travel purposes may be more willing to switch to public transit for their commute when faced with higher gasoline prices. This could be due to greater comfort or familiarity with the system. A dummy variable for any use of public transit in the two months prior to the NHTS survey is introduced in the analysis to see if such a difference exists and if it is significant.

IV. Data

The main data used are from the 2001 National Highway Travel Survey. This survey is conducted by the U.S. Department of Transportation's Federal Highway Administration and the Bureau of Transportation Statistics. It quantifies the travel behavior of the American public by gathering data on long-distance and local travel. In addition to the trip-related data, information on demographic, geographic, and economic characteristics are gathered. The surveys are presented in five data panels, representing (a) the household, (b) each person within the household, (c) each household vehicle, (d) characteristics of each day trip, and (e) characteristics of each long trip made by a person within the travel period. This analysis is performed with the individual as the unit of analysis, so all included data corresponds directly to the individual. The only exception to this is the measure of the fuel efficiency of the vehicle driven by the individual. The dependent variable being modeled is the annual miles the individual travels; for multi-vehicle households, these total miles could occur in different vehicles. To address this problem of selection of a vehicle, the individual is ascribed the fuel efficiency measure for the vehicle for which they are coded as the primary driver.

The 2001 NHTS contains a total of 160,758 observations; however, this analysis requires restrictions on which individuals can be included, significantly reducing the number of observations. Additionally, some alterations to the data had to be made to facilitate analysis. Household family incomes were stratified into ranges and coded into the data with a number that corresponded to this range, rather than a direct imputation of a specific figure. The variable was recoded using the mid-point of the ranges, but the highest range was top-coded at $100,000. This biases the mean downwards as higher incomes are given this top value for lack of a better estimate. A similar recoding was performed for education level, collapsing more specific categories used by the NHTS into four codes representing less than high school, high school grad, some college (including technical school and associate degrees), and college degree (or higher). This was performed to facilitate compatibility with the 2000 Census data that were also used. The detailed options for the method of travel to work were condensed into categories for private vehicle (car, SUV, van, pickup truck, other truck, RV, and motorcycle) and public transit (public bus, commuter train, subway/elevated rail, and street car).[1]

An individual's geographic location is described by the metropolitan statistical area (MSA), as defined by the U.S. Office of Management and Budget and based on Census data. These areas are defined for use in collecting and publishing federal statistics. An MSA consists of a core area containing a certain population (50,000 for the 2000 Census definitions which are used in the 2001 NHTS), defined by OMB standards, and surrounding communities that are highly related to the core through strong economic and social integration. The NHTS suppresses MSAs with fewer than one million residents for confidentiality reasons, and some respondents were not in an MSA. There are 52 MSAs represented in the 2001 sample.

[1] Hotel/airport shuttles, limousines, taxis, private boats, and private airplanes were not included as fitting either of these two definitions; however this excluded a negligible portion of the survey responses. Out of the 91,742 individuals who reported a method of commute, all of the above represented a combined 118 observations. Walking and biking were also excluded. These methods of commute constituted a total of 1.4% of those surveyed. Likewise, no distinction was made for those who carpool, representing 3.2% of those who commuted by private vehicle.

While presumably differing in urban structure from those cities offering only bus routes, metropolitan areas that feature subway/elevated rail and commuter rail are included in the analysis. The ultimate purpose of this paper is to discern if a difference exists among commuters in their choice of transportation mode depending on the ease of use of public transit and relative cost compared to driving a private vehicle. For many commuters in these large cities that contain public transit beyond bus routes, these alternate forms may be the most efficient and preferable option. Therefore their exclusion could obscure an important difference across metropolitan areas by ignoring this important option. The modeling of specific commutes for individuals based on observable characteristics is performed only within each city, so these differences will not affect how the predictions of commute times are formed. A city-specific comparison of the final results will further elucidate if there is any difference for the cities with these additional options. See Table 2 for a list of the included metropolitan areas and the presence of subway or elevated rail, indicated by an "X" in the second column.

Table 2: Included Metropolitan Areas

Metropolitan Statistical Area	Subway/Rail
Austin--San Marcos, TX	
Buffalo--Niagara Falls, NY	
Dallas--Fort Worth, TX	
Houston--Galveston--Brazoria, TX	
Milwaukee--Racine, WI	
Minneapolis--St. Paul, MN--WI	
New York--Northern New Jersey--Long Island, NY--NJ--CT--PA	X
Philadelphia--Wilmington--Atlantic City, PA--NJ--DE--MD	X
San Antonio, TX	
Washington--Baltimore, DC--MD--VA--WV	X

Data from the 2000 Census are also utilized. The Census provides many of the same demographic and geographic variables of interest that are included in the NHTS surveys. These data are used in the analysis to predict commute times for each individual in the NHTS based on these common variables. The one year of difference from 2000 to 2001 in the collection of the data presumably does not significantly alter the values of the variables enough to invalidate the compatibility of these datasets.

The other important data needed for this analysis are gasoline prices. The ACCRA Cost-of-Living Index provides the local price of unleaded, self-service (where available) gasoline on a quarterly basis for about 300 cities. Gas prices were collected for 2001, and the data for the core city in the MSA was used. Since the data are recorded on a quarterly basis and data are not available for each city in every quarter, a yearly average gas price is used. These gas prices are presented in Table 3.

Table 3: Local Gas Prices

Metropolitan Statistical Area	2001 Average
Austin--San Marcos, TX	$1.355
Buffalo--Niagara Falls, NY	$1.483
Dallas--Fort Worth, TX	$1.386
Houston--Galveston--Brazoria, TX	$1.353
Milwaukee--Racine, WI	$1.412
Minneapolis--St. Paul, MN--WI	$1.398
New York--Northern New Jersey--Long Island, NY--NJ--CT--PA	$1.635
Philadelphia--Wilmington--Atlantic City, PA--NJ--DE--MD	$1.625
San Antonio, TX	$1.253
Washington--Baltimore, DC--MD--VA--WV	$1.619

The specific metropolitan areas included in this analysis are those that are well-represented in the NHTS data and for which gas price data are available from the ACCRA Cost-of-Living Index. Individuals within these MSAs are only included if they are employed, self-reported as a driver, over the age of 25, and commuting to work using private modes of transportation. These limitations on the data are imposed because the proxy for public transit quality is created from predicted commute times. Therefore, this proxy is only valid for those who are in stable, full-time jobs with a regular commute, for which these conditions are meant to account. Furthermore, I am evaluating the possible change to public means of transportation for commuting, so the included individuals must currently be using private modes of transportation. The reported method of commute is for the week prior to the survey; the assumption is made that this is the individual's consistent choice for mode of transit. Non-response and missing data for certain key variables also require the exclusion of numerous observations from the analysis. The subset of the data used for the analysis contains 1225 usable observations, representing ten MSAs. Summary statistics by metropolitan area are shown in Table 4. A comparison of summary statistics for this subset of the NHTS with an "urban" subset of the NHTS (which includes only individuals in an identifiable MSA with a population greater than one million), the entire NHTS survey, and the 2000 Census data used in the analysis is presented in Table 5.

Data limitations necessitate the focus on these ten metropolitan areas. This raises concerns for sample selection bias if these cities are significantly different from those that had to be excluded because of data incompleteness. For example, four of the ten cities are in Texas, and all of the individuals in California cities were removed because of missing data. This raises questions over the differences that might exist in driving behavior and driver characteristics between these areas that might also affect individuals' preferences to use private transit regardless of gas price. There are intuitively perceived differences in city structures among large metropolitan areas that could be hypothesized to impact driving characteristics. While certain characteristics of the city, such as population density, are included in the analysis, these differences in driving preferences cannot be fully quantified or analyzed. The individual's actual commute time and predicted commute times help to control for this by controlling for their specific driving preferences when commuting and therefore allowing these preferences to enter the analysis.

As Table 5 indicates, the differences between the entire dataset and the subset of MSAs included in the analysis are not substantial. The inclusion of the urban subset of the NHTS provides a comparison to excluded MSAs that should be more similar to the included MSAs than the dataset as a whole. This urban subset excludes individuals whose MSA was suppressed because of size (less than one million residents) or not reported, and so it is composed of individuals likely facing more similar urban structures as those included in the analysis. A comparison of individuals in the excluded and included MSAs reveals that the individuals in the excluded metropolitan areas have somewhat lower incomes, shorter commute times and distances, and fewer annual miles traveled. However, the large standard errors associated with these averages indicate that these are not significant differences. I thus proceed with the caveat that the potential for selection bias certainly still exists, but the data do not allow me to detect substantial observable demographic differences that would indicate a significant problem.

Table 4: Summary Statistics by Metropolitan Area

Metro Area	Gas Price	Distance to Work	Time to Work	Yearly Miles	HH Size	HH Income	Obs
Austin--San Marcos, TX	$1.355	11.7	21.8	14,108.45	2.85	63697	71
Buffalo--Niagra Falls, NY	$1.483	10.56	20.08	12,514.46	2.73	$59,639	83
Dallas--Fort Worth, TX	$1.386	17.27	29.33	21,191.15	2.84	$70,470	218
Houston--Galveston--Brazoria, TX	$1.353	16.91	28.39	17,293.73	2.84	$64,668	196
Milwaukee--Racine, WI	$1.412	12.45	21.85	16,599.21	3.00	$64,266	126
Minneapolis--St. Paul, MN--WI	$1.398	14.40	22.86	11,071.43	2.43	$33,929	7
New York--Northern New Jersey--Long Island,NY--NJ--CT--PA	$1.635	17.19	29.47	16,140.67	3.08	$76,727	320
Philadelphia--Wilmington--Atlantic City,PA--NJ--DE--MD	$1.625	20.00	41.67	16,000.00	3.00	$100,000	3
San Antonio, TX	$1.253	11.49	19.54	15,843.08	3.12	$63,769	65
Washington--Baltimore, DC--MD--VA--WV	$1.619	15.82	28.26	14,743.93	2.84	$67,629	136

Table 5: Comparison of Summary Statistics

	2001 NHTS (Subset)	2001 NHTS (Urban)	2001 NHTS	2000 Census
Observations	1,225	63,132	160,758	14,081,466
Time to work	26.66	26.56	21.65	24.60
Distance to work	15.45	13.47	12.17	
HH vehicles	2.38	2.06	2.22	2.54
Income	$68,604	$58,419	$53,082	$61,816
HH size	2.92	3.23	3.18	3.19
Number of Adults	2.06	2.15	2.11	
Number of Workers	1.87	1.60	1.59	
Education level	some college	some college	some college	HS grad
Population Density	4,818.41	6,732.84	5,016.68	
Annual Vehicle Miles	16,706.45	12,730.64	16,413.74	
Cost per mile	0.0596	NA	NA	

Note: All summary statistics represent means.

V. Empirical Methodology and Results

The methodology employed is similar to that used in the existing literature to model the elasticity of demand for gasoline, employing independent variables that the literature has found to be significant when modeling vehicle miles traveled. It draws on the model developed by Haughton and Sarkar (1996), modified with additional demographic explanatory variables utilized in other studies. These variables are general demographic characteristics that serve as controls by allowing such factors as an individual's access to a privately-owned vehicle, financial and time constraints, type of occupation, and family characteristics to enter into the model. Using the identified metropolitan areas of interest, I evaluate how the price elasticity differs across areas with different quality of public transit systems.

In order to model the availability of public transit, a proxy for its quality is created from the predicted commute times for each individual. Opinion surveys have found that the most onerous parts of travel by public transit are the time spent waiting and the slower speed of travel (Su and DeSalvo, 2008). These concerns are more salient than the monetary cost arising from fares. When the travel times between public transport and private vehicle become more similar, it is predicted that a substitution to public transit will be more likely to occur to avoid rising gasoline prices. Since actual commute times can only be observed for the method the individual actually chooses, an estimate of the alternate time must be created to allow for this comparison.

The proxy was produced using the 2000 Census data to create predictions for the commute time by private transit and by public transit for each individual in the 2001 NHTS. These predictions were obtained using observable characteristics that have been shown to be correlated with the use of public transit and the distance to work, based on choice of neighborhood. It is assumed that individuals that appear similar in these observable respects will locate in similar parts of the city. In this way, their commutes will span a comparable section of the city, and thus the individuals will face a similar provision of public transit. This is validated by findings that general regions of cities can be defined by a similar income level, race, or household size (i.e. single-person or family), for example. These predicted travel times are assumed to model the commute time the individual would face for the method of travel they are not observed to take. Since the actual commute time by public transit cannot be observed for those taking private transit, the observables are meant to provide a better estimate of the public commute time than using city averages or another homogenous measure. A comparison of these mode-specific times allows the availability of public transit that each individual faces to be inferred from its time cost relative to private transit.

The following regression was used for these predictions:

$$\begin{gathered} TRANTIME = \beta_0 + \beta_1 HHINCOME + \beta_2 HHVEHCNT + \beta_3 AGE + \beta_4 MALE + \\ \beta_5 WHITE + \beta_6 HISPAN + \beta_7 EDLEVEL + \beta_8 HHSIZE + \varepsilon \end{gathered} \tag{1}$$

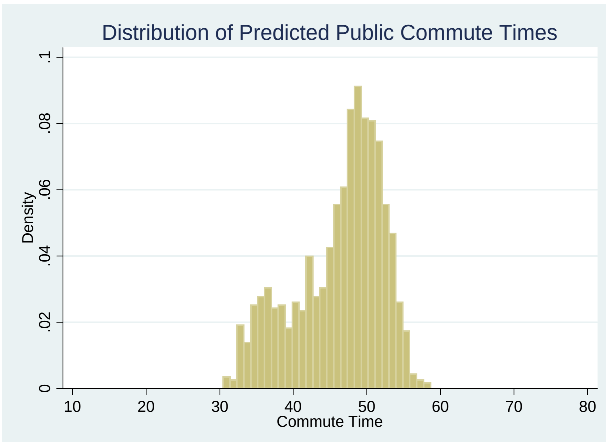
where TRANTIME is the time it takes to commute to work; HHINCOME is the total income of the household; HHVEHCNT is the number of vehicles owned by the household; AGE is the individual's age; MALE is a dummy variable equal to one if the individual is male; WHITE is a dummy variable equal to one if the respondent is white; HISPAN is a dummy variable equal to one if the respondent is Hispanic; EDLEVEL is the individual's highest level of education completed; HHSIZE is the total number of people in the individual's household; and ε is the error term.

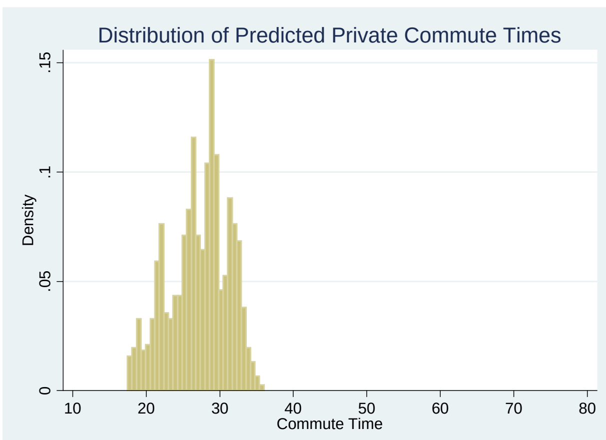
This regression was run twice for each metropolitan area. The first iteration included only individuals who traveled to work by private vehicle and the second iteration included only those who commuted by public transportation. The coefficients from the resultant equations were saved and used to create predicted commute times by private and public transit for each individual in the NHTS. The eight characteristics for each individual in the NHTS were entered into the appropriate two estimated commute time equations for the individual's metropolitan area. Each individual in the NHTS is therefore given a predicted commute time by private transit and a predicted commute time by public transit in addition to their actual observed commute time (by private transit). Figure 1 displays the distributions of these commute times. The mean of the actual commute times is similar to the mean for the predicted times by private transit at 26.656 and 27.146 minutes, respectively. The actual times have more variability, as would be expected due to idiosyncrasies that the prediction model cannot incorporate.

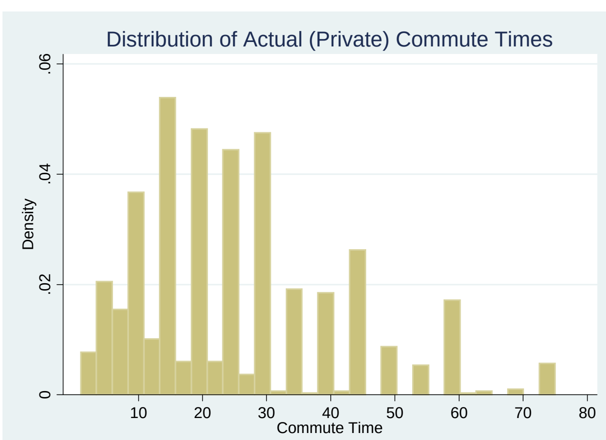
The predicted times are then used in the main regression in two different forms. The main specification uses the difference in the levels of the two predictions. The difference is calculated as the predicted private commute time minus the predicted public commute time. In the discussion below, this variable is labeled *Time diff*. This specification is intended to account for possible scaling factors. The second model uses the ratio of the predicted commute time by private transit to predicted commute time by public transit. This is discussed in the results as *Time ratio*. However, the *Time diff* is the preferred measure because of these scaling issues. For example, a worker may face commute times of 45 minutes by car and 90 minutes by bus versus another who faces a choice between 10 minutes by car and 20 minutes by bus. In this instance, the two individuals appear the same using the ratio of predicted times, but the first individual may always prefer private means of transit because of the much larger absolute time increase involved in the switch. The difference between the times is sensitive to these scaling differences and thus will not obscure this factor of the decision-making process when considering a change in the method of travel.

Figure 1: Distributions of Commute Times

	Mean	Std Dev
Fiitted Public	46.262	5.959
Fitted Private	27.146	4.009
Actual (Private)	26.656	18.02







Equation 1, the estimated commute time equation, uses observable characteristics to model mode-specific commute times for each individual in the NHTS; however, individuals may have idiosyncrasies that cannot be picked up in these predictions. The use of both predicted values measures the expected trade-off based on the experiences of a larger sample of representatives, who actually utilize one of the forms of transit, from each individual's city. Moreover, the actual commute time for the individual will be included as a separate regressor to attempt to account for these idiosyncrasies and scaling factors. This allows the actual time they are facing to add explanatory power and thus should control for some of the error in the predictions.

The theoretical framework of this analysis suggests a negative coefficient on the *Time diff* or *Time ratio*. An increase in either reflects a commute time for public transit closer to that obtained through private means of travel, and therefore better substitutability between the two. This should then reduce vehicle miles traveled (which by definition only measures travel by private vehicle). In the context of gasoline consumption, fewer vehicle miles traveled indicate decreased consumption. While the fuel efficiency of the private vehicle has to be assumed to be constant in the constraints of this model, it is not a reasonable assumption that people would change their vehicle to a less efficient one in the face of higher gas prices, making this connection between decreased miles and decreased gasoline consumption appropriate. When discussing the generic model, the abbreviation TIME is used, although the analysis was repeated using both *Time diff* and *Time ratio*. In discussing the results, the specific measure is indicated, although the analysis focuses on the *Time diff* as the more useful variable.

Having computed these predicted commute times, the main regression equation is performed. The initial model is run using an OLS regression, whose equation takes the form:

$$\ln(VMT) = \beta_0 + \beta_1 PRICE*TIME + \beta_2 PRICE + \beta_3 MPG + \beta_4 COMMUTETIME + \beta_5 POPDEN + \beta_6 X_1 + \ldots + \beta_{13} X_8 + \varepsilon \quad (2)$$

where the independent variable, ln(VMT), is the natural log of the annual vehicle miles traveled; PRICE is the local retail price of gasoline; PRICE*TIME is an interaction term between the local gas price and the proxy for public transit availability discussed above; POPDEN is the population density of the individual's census tract; COMMUTETIME is the individual's reported commute time to work (by private transit); X_1 through X_8 represent eight demographic and household descriptive variables; and ε represents the error term. The demographic variables are age, gender, race, size of household, number of drivers in the household, total household income, education level, and number of vehicles in the household. Vehicle miles traveled (VMT) measures all travel made by a private vehicle only, so a switch to public transit from private vehicle travel will not be obscured by using this dependent variable.

The TIME variable is interacted with PRICE to determine if the elasticity of vehicle miles traveled with respect to gas price varies with the quality of the substitute, public transportation. I expect this coefficient, β_1, to be negative. An increase in TIME indicates that the travel time by bus is closer to that for a car, implying that buses are more substitutable for cars than in another area. The individual has access to a relatively better public transit system than the other area.

This should make $\partial VMT/\partial Price$ more negative as the increase in the price of gasoline promotes a shift to public transit instead of automobile travel when the two are more comparable in time cost. Therefore, an increase in PRICE will induce a bigger reduction in gasoline consumption and fewer miles driven the more substitutable public transportation is for private transportation. This component would have policy relevance as it would recommend a concurrent increase in the availability of public transit along with an increase in price (as would be achieved, for instance, with a gas tax) to further reduce miles traveled than could be achieved with a gas price increase alone.

As noted earlier, data limitations require the assumption that the individual is driving the vehicle for which they are the primary driver for all of their yearly travel. However, the choice of vehicles is endogenous because an increased gas price may cause an individual in a multi-car household to choose a different, more fuel efficient vehicle for some of his yearly miles traveled. The efficiency of the vehicle may affect the individuals' choice of vehicle miles traveled and so there is really a joint choice between vehicle and miles. My assumption of vehicle usage provides the best estimate available without a more complicated model of this joint decision. Moreover, it is plausible to assume that this is the vehicle that the individual will continue to drive for the work commute as the alternate vehicles in the household are likely being used by other household members during the workday. The assumption of constant vehicle preference in this analysis thus allows a translation of decreased mileage into decreased gasoline consumption. The basic relationship between the decreased gasoline consumption and decreased vehicle miles traveled holds even if the assumption of consistent choice of vehicle is violated for part of an individuals' yearly travel, and so effects on vehicle miles found in this analysis correspond to decreases in consumption.

There still remains a possible source of endogeneity bias. Areas in which people drive more may also have higher gasoline prices. This could be due to the specific characteristics of the city, such as geographic location or urban structure, which make people prefer to drive more while also leading to higher gas prices. Simple simultaneity could exist if a larger demand in the city moves the city upward on the supply curve. Also, the city characteristics could be correlated with demand elasticity because individuals' preference to drive allows retailers to price gas higher in these areas. In order to account for this, an instrumental variables strategy is also used. State gasoline taxes are used to instrument for the endogenous retail price because the tax is hypothesized to be independent from vehicle miles traveled (since it is state-wide and determined independently from local driving considerations) but is correlated with gas price because it is one of the determinants of the retail pump price. The inclusion of only one year of data in the analysis precludes a fixed effects specification that would also address these city-specific characteristics, making a 2SLS model the best available option.

The results of the OLS and 2SLS regressions for the above model are presented in Table 6. Specifications (1) and (2) present the OLS regression using *Time diff* whereas (3) and (4) present 2SLS equations using *Time ratio*. *Time diff* is preferred over *Time ratio* because it involves a linear operation that is preferable when using predicted values. The predictions are noisy variables because of the variance of the error terms since only observable characteristics can be taken into account in their formulation. Therefore, the division by a noisy variable to calculate *Time ratio* can cause this ratio to behave badly for outlier individuals. The linear subtraction operator allows some of the error of the noisy variable to fall out into the error of the regression and so does not cause these same problems.

The use of *Time diff* in the 2SLS analysis generated an unintuitive positive coefficient on gas price, making this specification suspect, and so it is not included in the results table. In Specifications (3) and (4), using *Time ratio*, the coefficients on the gas price, miles per gallon, and the interaction of the price and *Time ratio* were not significant at any level. This indicates that although it performed better than the 2SLS with the *Time diff*, it still is not doing as good of a job explaining the relationship as the OLS model. Therefore, the OLS specifications presented in Specifications (1) and (2) provide the best fit when using this log-linear model.[2]

[2] Although modeled for every specification, the use of *Time ratio* in all other specifications is not reported as *Time diff* provides a better fit for the regression results in addition to better supporting the theoretical framework of the time trade-off between the two modes of transit. Additionally, other specifications were attempted, most notably using cost per mile as a regressor rather than gas price and miles per gallon separately. While this follows the specifications used in the majority of the literature, the inclusion of the two variables separately better fits this dataset and so is used instead. A direct measure of miles per gallon is available, unlike much of the literature that used different methods to impute a mileage estimate based on type of vehicle or vehicle choice probabilities for multi-car households.

Table 6: Regression Results
Dependent Variable: ln(VMT)

	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
Price* Time diff	-0.0111**	-0.0119**		
	(0.00469)	(0.00474)		
Gas Price	-0.521**	-0.493**	-0.116	-0.0986
	(0.213)	(0.214)	(0.953)	(0.969)
Miles per Gallon	-0.00426	-0.00426	-0.00399	-0.00397
	(0.00328)	(0.00328)	(0.00354)	(0.00353)
Hh Income	2.43e-06**	2.56e-06**	2.71e-06**	2.79e-06**
	(1.00e-06)	(1.01e-06)	(1.13e-06)	(1.11e-06)
Driver Count	-0.153***	-0.153***	-0.155***	-0.154***
	(0.0451)	(0.0451)	(0.0453)	(0.0455)
Hh Vehicle Count	0.0797***	0.0786***	0.0794***	0.0786***
	(0.0273)	(0.0273)	(0.0287)	(0.0286)
Education Level	0.0106	0.0155	0.00947	0.0134
	(0.0309)	(0.0311)	(0.0358)	(0.0370)
Age	-0.00903***	-0.00918***	-0.00807***	-0.00814***
	(0.00235)	(0.00235)	(0.00252)	(0.00255)
Male	0.337***	0.337***	0.340***	0.341***
	(0.0490)	(0.0490)	(0.0669)	(0.0671)
Commute Time	0.0118***	0.0119***	0.0123***	0.0124***
	(0.00129)	(0.00129)	(0.00134)	(0.00133)
White	0.132**	0.133**	0.142*	0.143*
	(0.0600)	(0.0600)	(0.0769)	(0.0767)
Population Density	-2.27e-05***	-2.10e-05***	-2.03e-05***	-1.94e-05***
	(4.26e-06)	(4.43e-06)	(5.90e-06)	(5.61e-06)
Hh Size	0.0278	0.0269	0.0363	0.0352
	(0.0235)	(0.0235)	(0.0254)	(0.0257)
Rider*Price*Time Diff		0.00300		
		(0.00218)		
Price*Time Ratio			-0.553	-0.545
			(0.562)	(0.561)
Rider*Price*Time ratio				-0.0599
				(0.0830)
Constant	9.735***	9.662***	9.812***	9.770***
	(0.300)	(0.304)	(0.880)	(0.908)
Observations	1223	1222	1223	1222
R-squared	0.186	0.187	0.183	0.184

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

The difference between these two specifications is the inclusion of an additional interaction variable in Specification (2). This second interaction term, RIDER*PRICE*TIME, takes into account a possible difference among those who used public transportation at any time for any trip purpose in the two months prior to the survey. A dummy for public transportation usage is interacted with local gas price and *Time diff*. These individuals may be more willing to utilize public transit, whether because they are more familiar with the system or just more comfortable using it, than other commuters. This would make them more inclined to switch the mode of travel for their commute than other workers in the face of higher gasoline prices. The expected sign on the coefficient is positive, as is found in the model. The derivative with respect to gas price is this positive coefficient times the negative *Time diff*, thus reducing overall miles traveled for the individuals who used public transit. This provides a further reduction in vehicle miles traveled relative to the effects of gas price and PRICE*TIME for those who have not used public transit at any time in the past two months.

The inclusion of this variable slightly alters the magnitude of the other coefficients without changing any signs or significance levels. It reduces the magnitude of the coefficient on PRICE while increasing the magnitude of the coefficient on PRICE*TIME. While it carries the expected positive sign, it is not significant. While altering the magnitude of the coefficients on PRICE and PRICE*TIME, this change is not great and the significance level of each is not affected. Similarly, it does not much alter the fit of the model or the subsequent analysis of individual elasticities, indicating that it is not providing much additional explanatory power. This may indicate that there is no difference in people's willingness to switch to public transit based on prior experiences riding public transit. This is evidence that people may be equally likely to switch in response to a change in gas price. However, in this sample, 15.85% of the respondents are flagged as having used public transit at any time. This interaction term may not provide substantial extra explanatory power if this is too small of a population to allow this relationship to significantly affect the model even if the relationship does exist.

Specification (1), without this RIDER*PRICE*TIME interaction, thus provides the best specification. The coefficient on PRICE carries the expected negative sign and is also statistically significant at the 5% level. A one-cent increase in gas price is expected to decrease vehicle miles traveled by 0.521%. Miles per gallon has a negative coefficient, indicating that a one mile per gallon increase in fuel efficiency is associated with a decrease in yearly miles traveled by 0.426%. This likely captures the fact that those who buy fuel efficient cars also drive less, not necessarily that high fuel efficiency causes people to drive less. This is not statistically significant though.

The included demographic regressors take the expected signs for those that have expected relationships to vehicle miles traveled. Household income, the number of household vehicles, education level, commute time, and household size are predicted to increase vehicle miles traveled. Education and household size are the only two demographic variables that are not statistically significant. Additionally, population density and number of drivers in the household have negative coefficients, reflecting that increases in either are expected to decrease miles traveled. Both of these are statistically significant at the 1% level. This is an important finding for population density as it affirms the theory that those located in denser areas may have everyday destinations that are closer by, reducing the necessary yearly miles driven. The number of drivers could be expected to have a negative effect as certain household miles that are not associated with an individual's work, such as errands and family trips, can be spread over more drivers. Lastly, males and whites are predicted to travel more miles, and increases in age are predicted to decrease miles. Age and sex are significant at the 1% level while race is significant at the 5% level.

The negative coefficient on the interaction of PRICE and TIME indicates that people are more sensitive to changes in gas prices when public and private transit are more substitutable. Gas price alone has a statistically significant predicted negative effect on vehicle miles traveled, as discussed above. However, the interaction picks up the combined effect of gas price and public transit availability because it allows the derivative of the regression equation with respect to one of these variables to depend on the value of the other. It is this interaction that shows that the sensitivity to gas price depends on the relative quality of public transit in the individual's area. The coefficient on this interaction term is -0.0111, and it is significant at the 5% level. Therefore, it can be concluded that individuals further reduce their miles traveled in response to an increase in the gas price in relation to the substitutability of public transit for their work commute, presumably using public transit in place of their current private means of commuting.

The model was also analyzed using a linear specification, making the dependent variable vehicles miles traveled but otherwise using the same model presented in Equation 2. This model was similarly run using both OLS and 2SLS specifications, and the results are presented in Table 7. Specifications (6) and (8) include the RIDER*PRICE*TIME interaction. Again, the inclusion of this variable increases the magnitude of the coefficient on PRICE*TIME while decreasing the magnitude of the coefficient on PRICE, but does not significantly affect any of the results. With respect to the 2SLS specifications, the F-test indicates that the instrument is relevant. The inclusion of only one instrument prevents the use of a J-test to test for exogeneity, thus forcing reliance on the assumption that state gas taxes will not co-vary with the error. This is based on the reasoning that state gas taxes will be independent of local driving conditions and preferences that affect the local gas price. The use of instrumental variables, while significantly affecting the coefficients on gas price, miles per gallon, and PRICE*TIME, also reduces their significance. This is because the use of the instrument introduces noise into the prediction of the endogenous variable gas price and therefore reduces the explanatory power of the model. Therefore, I rely on the OLS estimates.

Overall, the use of the log-linear functional form provides a better fit because the data for vehicle miles traveled is skewed. The log improves the fit of the model by linearizing this relationship. Also, this functional form provides the highest R-squared value and has more statistically significant coefficients than the linear model. The regression results presented in Specification (1) of Table 6, utilizing an OLS specification with *Time diff*, are therefore used for the following stages of the analysis.

Table 7: Regression Results
Dependent Variable: VMT

	(5) OLS	(6) OLS	(7) 2SLS	(8) 2SLS
Price* Time Diff	-355.7***	-370.9***	-377.7***	-389.6***
	(91.39)	(92.24)	(103.4)	(98.56)
Gas Price	-13626***	-13094***	-22032	-21795
	(4147)	(4167)	(29478)	(29929)
Miles per Gallon	-4.677	-4.500	14.70	15.27
	(63.80)	(63.80)	(93.25)	(93.05)
Hh Income	0.00125	0.00359	0.00786	0.00995
	(0.0195)	(0.0196)	(0.0308)	(0.0294)
Driver Count	-2834***	-2822***	-2849***	-2841***
	(877.1)	(877.2)	(881.4)	(882.6)
Hh Vehicle Count	991.2*	970.3*	920.8	903.1
	(531.2)	(531.6)	(590.3)	(581.7)
Education Level	-1245**	-1156*	-1268**	-1195*
	(602.0)	(605.5)	(615.9)	(635.6)
Age	-136.8***	-139.8***	-137.5***	-139.8***
	(45.76)	(45.84)	(45.95)	(46.31)
Male	6033***	6037***	6040***	6043***
	(953.0)	(953.1)	(958.7)	(958.9)
Commute Time	194.4***	197.2***	199.7***	202.1***
	(25.02)	(25.10)	(31.72)	(30.49)
White	1155	1171	1525	1549
	(1168)	(1168)	(1801)	(1794)
Population Density	-0.312***	-0.281***	-0.266	-0.240
	(0.0830)	(0.0863)	(0.187)	(0.165)
Hh Size	850.1*	833.9*	897.0*	885.1*
	(456.6)	(456.8)	(500.2)	(505.0)
Rider* Price* Time Diff		56.71		45.92
		(42.49)		(64.26)
Constant	29042***	27677***	39327	38465
	(5834)	(5923)	(36680)	(37820)
Observations	1223	1222	1223	1222
R-squared	0.135	0.136	0.131	0.132

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

VI. Calculation of Elasticities

Elasticities of demand for vehicle miles traveled, and therefore gasoline, are calculated for each individual and for each city. These elasticities are calculated using the following equation:

$$(\partial \ln(VMT)/\partial PRICE)*PRICE = (\beta_1 TIME + \beta_2)*PRICE. \quad (3)$$

The elasticities for the individuals are calculated using the mean of the observations and then repeated using the medians for the necessary variables because of slight skewness of the data. These elasticities are -0.4544 and -0.4297, respectively, which fall within the range of the elasticities in the literature. The correlation between an individual's specific elasticity of demand and *Time diff* is -0.825. The elasticities for the best linear specification (Specification (5)) are calculated as

$$(\partial VMT/\partial PRICE)*(PRICE/VMT) = (\beta_1 TIME + \beta_2)*(PRICE/VMT). \tag{4}$$

These are more elastic at -0.6017 when using the means and -0.6298 when using the median values. These latter calculations reflect the impact of outliers that have very few yearly miles traveled, even though they report using private transit to get to work. Some of these outliers also have very short commutes even though they use private vehicles to commute. The outliers could alter these elasticity calculations that utilize the level of yearly miles traveled by reducing the mean and median of yearly miles traveled. This reduces the denominator in the elasticity calculation and thus inflates the figure. This further motivates the log-linear functional form as the best result, as concluded earlier.

This specification (Specification (1) in Table 6) was therefore also used to calculate the city-specific elasticities. The elasticities are calculated using Equation 3, with the city-specific mean of TIME. These are presented in Table 8 along with the average *Time diff* for all the individuals in these metropolitan areas. These elasticities range from -0.546 for the Washington, DC metropolitan area to -0.378 for San Antonio, TX. The presence of a subway or elevated rail system did not seem to affect the elasticities for the three cities of Washington, DC, New York, NY, and Philadelphia, PA in comparison to those without rail systems. This is evidenced by the lack of clustering in the rank ordering of the ten city elasticities. Those cities with a smaller average *Time diff*, indicating a better trade-off between public and private transportation, have more elastic price elasticities of demand than those with the larger average *Time diffs*. The correlation between the city's elasticity of demand and average *Time diff* is -0.6817.

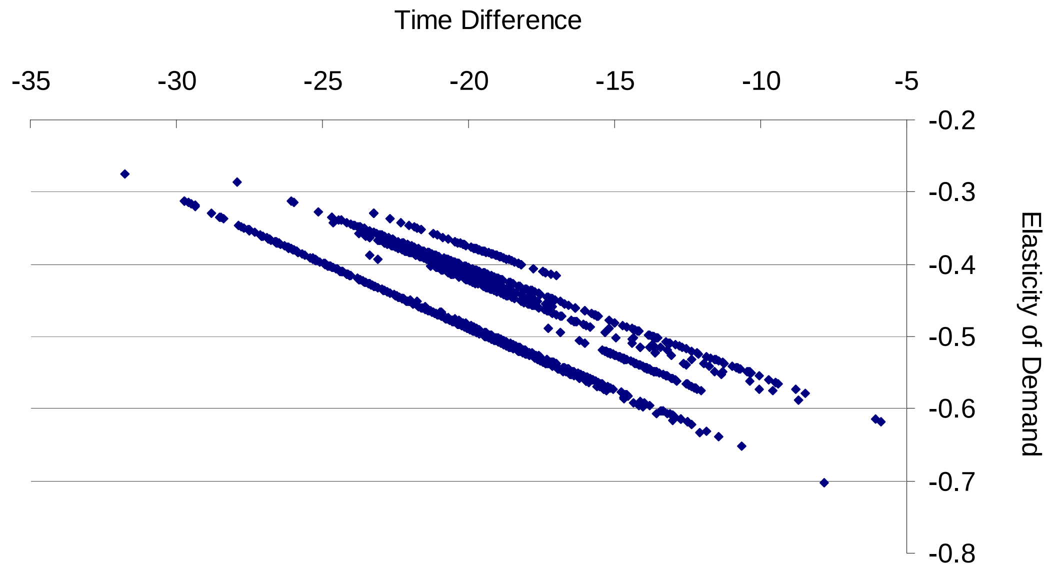
Figure 2 represents this relationship. Each line corresponds to a city and therefore a given price of gasoline. It exhibits the importance of public transit in affecting individuals' responsiveness to price. The slope of the line illustrates the decrease in the magnitude of *Time diff* necessary to achieve a certain sensitivity of vehicle miles traveled to gas price. A reduction in the magnitude indicates that public transit becomes a better alternative to private transit because the commute time associated with public transit is closer to the time necessary when using private transit.

This supports the hypothesis of this analysis that those commuters facing a better time trade-off between commuting to work by private vehicle and by public transportation are more responsive to increases in the gas price. The analysis includes only workers commuting by private means, and the majority of them do not report using public transit for other trips, so the conclusion from the theoretical framework is that these individuals are likely to decrease their miles traveled through a substitution of the method of travel for their commute when the two methods are more similar in transit time. The strong correlation of city-specific elasticity with the quality of the public transit system adds confidence that this decrease is not simply from the reduction of other vehicle trips, in which case elasticities should be similar across areas and not related to the associated *Time diff*.

Table 8: City-Specific Elasticities

Metropolitan Area	Elasticity (at mean)	Mean Time Diff
Washington--Baltimore, DC--MD--VA--WV	-0.546	-16.556
Buffalo--Niagara Falls, NY	-0.535	-14.431
Minneapolis--St. Paul, MN--WI	-0.534	-12.551
Austin--San Marcos, TX	-0.511	-12.976
Philadelphia--Wilmington--Atlantic City, PA--NJ--DE--MD	-0.464	-21.218
New York--Northern New Jersey--Long Island, NY--NJ--CT--PA	-0.461	-21.521
Milwaukee--Racine, WI	-0.448	-18.339
Dallas--Fort Worth, TX	-0.413	-20.078
Houston--Galveston--Brazoria, TX	-0.395	-20.603
San Antonio, TX	-0.378	-19.737

Figure 2: Relationship between *Time diff* and Elasticity of Demand



It is possible that as commuters switch to public transit, road congestion is reduced. This would reduce travel time for those continuing to use private means of transportation. However, the strong correlation between the individual's difference in predicted commute times and elasticity of demand implies that those already facing better trade-offs are the first to switch. Therefore a further increase in the *Time diff* because of a lessened private vehicle commute time would not affect these individuals. Over a longer timeframe, those who made the switch may switch back if facing a shorter private commute time because of the decrease in road congestion. This implies that there may be differing effects as the feedback from initial switches to public transit affect future evaluations of the time trade-off in relation to the current gas price.

The analysis of the elasticities is extended to better describe the appellation of "good" versus "bad" to a public transit system. Two subgroups are created. The first contains the individuals with values of *Time diff* lying at least one standard deviation below the mean. This gives a group of individuals with relatively poor trade-offs between public and private transit because of the greater size of the difference in predicted commute times. Since *Time diff* is calculated as the private commute time minus the public commute time, a larger magnitude indicates that public transit takes relatively longer and therefore is a poorer substitute. This subgroup has an average price elasticity of -0.3790 when using the mean values and -0.4095 when using the median values for these individuals. In the same manner, the second group contains the individuals with *Time diffs* greater than one standard deviation above the mean, reflecting better trade-offs. This group has elasticities of -0.5493 using mean values and -0.5478 using median values. Those individuals facing poorer quality public transit have more inelastic demands than individuals as a whole while those facing the best time trade-offs have more elastic demands for gasoline. This further supports the link between the availability of superior public transit options and greater responsiveness to gas prices found in the city-specific analysis and high correlations between elasticity of demand and *Time diff*.

A final policy implication can be drawn from the analysis of these different elasticities. The statistical significance of the interaction term between gas price and *Time diff* indicates that these two have a significant combined effect on vehicle miles traveled. The trade-off in commute times between public and private methods of travel reduces the predicted miles traveled further than the negative effect resulting from the gas price alone. Similarly, the range of elasticities among those cities and individuals facing these different trade-offs supports the conclusion that this trade-off impacts the elasticity of demand and that the two therefore work in conjunction as well as separately.

One further piece of support is created from modeling an increase in the price of gas due to a larger gas tax and an increase in *Time diff*, reflecting better substitutability of travel modes. A one standard deviation increase in *Time diff* from the existing mean and a $.50 cent increase in the gasoline tax are used. This amount for the gas tax is chosen as a middle point between the $1 increase some economists call for (for example, see Mankiw (2006) and his online list of fellow economists and policy-makers who support such a tax, available at http://gregmankiw.blogspot.com/2006/09/rogoff-joins-pigou-club.html) and the lower estimates of optimal taxation levels found in some existing studies. Such changes increase the elasticity for individuals from -0.4544 to -0.5858 when using the mean values and from -0.4297 to -0.6227 when using the median values. When the gas tax is modeled without the corresponding improvement in the quality of public transit, these elasticities are -0.5013 using the means and -0.5347 using the medians. Gas price alone has a discernibly smaller impact on individuals' sensitivity than this combined effect. These results are summarized in Table 9.

Table 9: Individual Elasticities

	At Mean	At Median
All Individuals	-0.4544	-0.4297
One Std Dev above Mean Time Diff	-0.5493	-0.5478
One Std Dev below Mean Time Diff	-0.3790	-0.4095
$.50 Increase in Gas Price	-0.5013	-0.5347
Plus One Std Dev Increase in Time Diff	-0.5858	-0.6227

All of these findings combine to imply that a policy of raising the gasoline tax as a tool to decrease gasoline consumption may prove more effective in areas with better public transportation options. By extension, areas with poorer relative public transit systems could see greater success in reducing consumption by undertaking such a gas tax increase in conjunction with projects to increase the public transit infrastructure. This lends support to the focus on infrastructure spending in the ARRA stimulus bill as these improvements could continue to provide benefits beyond immediate job creation by reducing the externalities associated with driving.

VII. Conclusion

The existing literature on the relationship between gas prices and consumption of gasoline consistently finds somewhat inelastic price elasticities of demand. While some studies differentiate between short-run and long-run elasticities, finding more elastic demands in the long-run, these studies use state- and national-level data in their calculations. Additionally, they do not consider the role other transportation options may play in consumers' decisions. This study addresses the differences that arise in a city-level analysis that also controls for the quality of public transit. The quality of public transit is estimated from the difference between the commute times an individual is predicted to face when traveling by private transit and by public transit.

These predicted commute times incorporate observable attributes from detailed Census information to develop richer predictions and control for sorting.

The analysis supports the theory that commuters facing a better public transit system will be more responsive to changes in gas prices by reducing their yearly miles traveled in a private vehicle. This also corresponds to a decrease in gasoline consumption. The statistical significance of the interaction term between the gas price and *Time diff* indicates that public transportation infrastructure has an effect on individuals' choice of yearly miles traveled beyond the change induced by the gas price alone. In the theory of the model, this decrease is due to a substitution to public transit for work commutes, trips that cannot be quickly or easily altered to avoid higher gas price.

The elasticity of demand for the aggregate sample is estimated as -0.4544 or -0.4297, depending on the use of mean or median values, respectively. These fall within the range of the existing literature, although slightly in the upper range. However, both the analysis at the city-level and that for the individuals facing the largest and smallest commute time differences indicates that there are substantial differences in elasticities related to the quality of the public transit alternative. Cities that provide better average public transportation infrastructures, measured by a smaller difference in predicted commute time between the two modes, have more elastic demands than those with poorer average trade-offs for commuters. The correlation between city-specific *Time diff* and elasticity of demand is -0.6817. Similarly, individual commuters facing a smaller difference in commuting times between the alternate modes are more responsive to the price of gasoline by decreasing private vehicle miles traveled. The correlation between an individual's *Time diff* and elasticity of demand is -0.825.

The significance of the combined effect of gasoline price and the quality of the public transit system has policy implications for the effectiveness of an increase in gas price through the implementation of a higher gasoline tax. Such a tax would have greater efficacy in reducing miles driven, and therefore reducing gasoline consumption, in areas where public transportation provides a more viable transit option for workers. In areas with poorer infrastructure, an improvement in the public transit system in addition to the higher gas tax could improve the ability of the tax to decrease gasoline consumption. The reduction of consumption is desirable because of the associated negative externalities and public concern with price fluctuations. These findings illustrate the importance of effective use of the stimulus money in the 2009 American Recovery and Reinvestment Act. The $8.4 billion allocated for public transit projects could make a gas tax, promoted for its benefits in reducing consumption, more effective if implemented. Even without such a tax, the infrastructure improvements could induce greater use of public transit in times of high gas prices, as seen recently.

Certain extensions could build upon the findings of this analysis. The inclusion of more cities would mitigate concerns about sample selection bias and could improve the robustness of the results. Similarly, an update of the analysis with more recent data (such as the 2008 NHTS to be released in September 2009) would allow the introduction of city fixed effects. This data might also capture greater changes in behavior because of the larger swings in gasoline prices that occurred in the data collection period and the sizable real increases from 2001 gasoline prices. This analysis indicates that the quality of public transit plays a role in commuters' sensitivity to gas prices, and greater work on this issue could provide important insights into the value of constructing convenient public transit systems.

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