The Impact of Rising Gasoline Prices on US Public Transit Ridership

Christopher Blanchard

Advisor: Professor Chris Timmins

Duke University
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Abstract

This paper analyzes the impact of increasing fuel prices on public transit ridership in the United States. Using regional gasoline prices and transit ridership and supply figures from 218 US cities from 2002 to 2008, I estimate the cross-price elasticity of demand for four modes of transit with respect to gasoline price. I report how these estimates vary between cities and test to see if these cross-price elasticities have changed over time. I find a cross-price elasticity of transit demand with respect to gasoline price ranging from -0.012 to 0.213 for commuter rail, -0.377 to 0.137 for heavy rail, -0.103 to 0.507 for light rail, and 0.047 to 0.121 for bus. These estimates vary significantly between cities but are not highly correlated with urban population size. Additionally, I find evidence suggesting that the cross-price elasticity has increased over this time period for commuter rail, light rail, and motorbus transit.

1. Introduction

The average price of gasoline in the United States has risen significantly over the past several years, increasing from $1.148 per gallon in January 2002 to its peak of $4.114 in July 2008[1]. During this period, aggregate public transit ridership has grown at an increasing rate[2] while the growth of total vehicle miles traveled slowed to a halt and even decreased in 2007 and 2008[3].

The increase in transit ridership and decrease in vehicle miles traveled is particularly notable as private vehicle use in the United States had been steadily growing since the 1940's (St. Clair 1981). The 2001 National Household Transportation Survey found that 87.9% of all commutes to work were by private vehicle, compared to only 4.7% by public transit (Pucher, 2003). As private vehicles and public transportation are substitutes, an increase in gasoline prices makes public transportation relatively cheaper than driving and is expected to increase transportation demand. Many other factors also determine travel mode choice, but the recent surge in gasoline prices has received a lot of attention from national and local media outlets as the driving force behind the shift in travel behavior. The relevant literature varies widely regarding the size and significance of gasoline prices' effect on ridership and does not support any single conclusion.

This study comprehensively analyzes the nature of the relationship between gasoline prices and public transit ridership in the United States, aiming to estimate the extent to which gasoline prices have determined transit demand since 2002. To accomplish this, the cross-price elasticities of four modes of public transit demand with respect to gasoline price are estimated using a nationwide panel dataset. A cross-price elasticity of demand is

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1 US Energy Information Administration, average gasoline price estimate - all grades
2 American Public Transportation Association, Ridership Reports Archive
3 US Federal Highway Administration, Travel Volume Trends

a measure of the percent change in one goods' demand caused by a 1% change in another good's price. In this case, I will estimate the change in transit demand caused by a 1% change in gasoline price. To allow for comparison, I employ a procedure similar to previous research, but using a dataset offering two advantages. First, I use panel data containing monthly observations of supply and demand from 218 cities across the nation, many more cities than any previous study of US transit ridership. Second, I include observations of the recent rise in gasoline prices, enabling me to see how ridership responded in these unusual circumstances. Also, to put the elasticity estimates into better context, I research how these estimates vary across cities and determine whether or not this elasticity has remained constant over time. For the entire time period, I estimate cross-price elasticities of .087 for commuter rail, -0.012 for heavy rail, .100 for light rail, and .063 for motorbus. These estimates tended to increase with population and varied significantly between cities, but not in a uniform manner. Finally, the cross-price elasticity significantly increased during the time period in three modes: commuter rail, light rail, and motorbus. This suggests that consumers became increasingly sensitive to gasoline prices as those prices reached higher levels during the latter half of the period of observation.

A more refined understanding of the relationship between gasoline price and public transit will be useful to two audiences: public transit agencies and policy makers. Public transit agencies are especially concerned with the price of gasoline as it partially determines both their costs and level of service demanded. An increase in gasoline price makes service provision, especially buses, more costly, while it simultaneously raises demand. Winston and Maheshri (2006) note that on average, fares only collect 40% of transit's operating costs, meaning increased service provision during periods of high gasoline prices would not be sustainable, even with a reasonable increase in fares. A comprehensive knowledge of how changes in gasoline price affect demand, especially the relative impacts on different modes of transit and the price sensitivity of new riders, will help transit authorities respond to gasoline prices with optimal levels of service and fares.

Policy makers would benefit in two ways from a better understanding of how gasoline prices affect travel mode choice. First, there are several social costs associated with vehicle use, namely greenhouse gas emissions, congestion, highway upkeep, foreign oil dependence, and traffic accidents (Murphy and Delucchi, 1998). Insight into the factors that have led individuals to reduce vehicle use can guide future policy aimed at encouraging similar behavior. Second, when considering plans for constructing or improving transit infrastructure, policy makers will be aided if they know how demand for each mode of transit in a given city is likely to respond to a change in gasoline price, or alternatively, the extent that a given city would support a transit system at various levels of gasoline prices.

The rest of this paper is organized as follows. Section 2 reviews the existing research on transit ridership, particularly papers measuring the effects of gasoline prices. To estimate the impact of gasoline prices on transit ridership, a specification of public transit demand is developed. Section 3 addresses common econometric problems and develops empirical specifications. Then, using a panel dataset of US transit ridership, section 4 estimates cross-price elasticities for commuter rail, heavy rail, light rail, and motorbus transit demand, allowing the estimates to vary by city, metropolitan population, and over time. Finally, section 5 concludes.

2. Literature Review

Public transit has been heavily researched by economists, urban transportation planners, and policy researchers. Using both cross-sectional and time-series analysis, researchers have identified and measured many factors that determine transit ridership; however, few papers study the effect of gasoline prices on transit ridership. Of the papers that include gasoline prices, some find a significant positive relationship that varies widely by city, mode of transit, and empirical specification, whereas other studies find no significant relationship. To provide the context of gasoline prices' role in the literature, this section begins with an overview of the major determinants of transit ridership. Then, the results and methodologies of papers which measure the impact of gasoline prices are reviewed.

2.1 Overview of the Factors Affecting Transit Ridership

The transit literature has identified many factors that influence transit demand. Before looking at gasoline prices' effect, one must assess the possibility that these other factors are responsible for the recent change in travel behavior. Summarizing the transit literature, Taylor and Fink (2002) divide the factors affecting transit ridership into two broad categories: internal and external. Internal factors are determined by a transit system's operators and include fare, level of service, and quality of service. External factors are largely exogenous to transit system's managers, and can be further categorized as geographic, demographic, or economic.

The effects of internal factors, specifically transit pricing, are well studied. Holmgren (2007), Litman (2004), Taylor and Fink (2002) and Goodwin (1992) review many of these studies. Using estimates from 81 studies, Holmgren finds a mean own-price elasticity of -.38, signifying that a 1% increase in transit fares will decrease demand by .38%. He notes though, that this estimate ranges from -.009 to -1.32, meaning transit can range from being almost perfectly inelastic to greater than unit elastic. Litman reports a similar range of elasticity estimates, along with the insight that large cities have a smaller price elasticity (due to more transit-dependant riders), fare increases affect ridership more than fare decreases, elasticities differ between modes of transit, and long-run elasticities are roughly twice the magnitude of short-run elasticities. These factors, among others, are very likely to affect estimates of cross-price elasticities as well, albeit in potentially unique ways. The amount of service provided, generally measured in vehicle revenue miles, has been found to have a significant positive relationship with ridership. Vehicle revenue miles represent the distance a transit vehicle travels while in service, and is commonly used as a proxy for transit supply. Holmgren finds an average elasticity with respect to vehicle revenue kilometers of .72, meaning that for every 1% increase in the number of hours transit vehicles are in service, ridership goes up .72%. Service quality factors such as speed, reliability, safety, cleanliness, ease of use, crowdedness, and route orientation have also been found to significantly impact ridership, however they are relatively more difficult to measure. The literature is not conclusive about whether riders are more sensitive to changes in service quality or service quantity. Taylor and Fink and Cervero agree that service characteristics are more important than fares, and more generally, external factors have a larger impact on transit ridership than internal factors. On average, fares have increased since 2002, so transit pricing is not likely to explain the rise in ridership levels. Service levels have risen since 2002, so they could potentially explain the increase in ridership and should be accounted for. Presumably, service quality has increased as well, but barring any dramatic changes in the transit infrastructure, this variable can be assumed to have exerted a constant upward influence on ridership in a similar manner as frequent service expansions.

External factors impact transit demand by altering the perceived relative costs and benefits of transit versus vehicle travel. Taylor and Fink (2003) note that geographic factors such as the area of urbanization, urban form, topography, and climate all contribute to travel mode choice. Demographic factors can have a strong impact on one's predisposition to ride public transit. High percentages of college students, immigrants, and Democrats are all found to be positively correlated with transit demand, whereas percent living in poverty and percent of households with a vehicle have a negative relationship with transit ridership. Economic factors such as income and unemployment level also have been found to have a strong effect on public transit ridership (Taylor et al. 2008, Thompson and Brown, 2006). Increases in average household income lead to decreases in transit ridership,[4] and controlling for income, unemployment has a negative impact on transit demand. This is due to the fact that commutes to and from work comprise a significant portion of one's demand for transportation, so being jobless causes people to have a large reduction in overall transportation demand. The geographic, demographic, and economic factors discussed above may play a significant role in explaining the increase in ridership and must be addressed as well.

[4] Having a negative income elasticity of demand makes public transit an inferior good.

2.2 Measuring the Effect of Vehicle Operating Costs on Transit Ridership

Another economic variable that partially determines transit demand is the cost of operating a motor vehicle. Highway and bridge tolls have been found to significantly impact transit demand, causing a .37% increase in ridership for every 1% increase in tolls (McLynn and Goodman, 1973). Also, increases in parking price and decreases in parking availability have been found to significantly increase transit demand (Moral and Bolger, 1996). Finally, gasoline prices theoretically impact transit demand in a similar fashion, but estimates of this effect vary widely between studies. Cross-sectional studies, such as Taylor and Miller (2008) and Kohn (2000) tend to find that gasoline price has an insignificant impact on ridership. Taylor and Fink (2008) explain that this result is caused by a lack of sufficient cross-sectional variation in gasoline price.

2.2.1 Time-Series Estimates of Cross-Price Elasticities

The studies that use time-series or panel data to measure the cross-price elasticity of transit ridership with respect to gasoline price are summarized in Table 2.1 below.

Table 2.1 Results from Previous Studies of the Impact of Gas Prices on Transit Demand (from Mattson 2008)

Study	Short-Run	Long-Run	Not Defined	Years	Notes:
Agthe and Billings 1978			0.42	1973-1976	Tucson, AZ buses
Wang and Skinner 1984	0.08-0.80			1970-1980	7 US Cities
Doi and Allen 1986			0.112	1978-1984	Philadelphia urban rail
McLoed 1991			insignificant	1958-1986	Honolulu, HI bus
Voith 1991	1.05	2.69		1978-1986	Philadelphia urban rail
Currie and Phung 2007			0.04	1998-2005	US aggregate data
Haire and Machemehl 2007			0.24	1999-2006	5 large US cities
Mattson 2008			.08 - .50	1999-2007	11 Midwest towns' bus transit

One of the first studies is Agthe and Billings (1978), which estimates a cross-price elasticity of .42 using Tuscon, AZ bus transit data from 1973 to 1976. Wang and Skinner (1984) use time-series data from transit agencies in seven US cities from 1970 to 1980 and estimate cross-price elasticities ranging from .08 to .80. Doi and Allen (1986) use a time-series dataset ranging from 1978 to 1984 to estimate the cross-price elasticity for an urban rail rapid transit line in Philadelphia, finding a result of .112. In a study of Honolulu bus ridership from 1958 to 1986, McLeod (1991) finds that gasoline prices did not have a significant effect, despite his hypothesis to the contrary. Finally, Voith (1991) uses a panel dataset of rapid transit ridership figures from 129 stations in Philadelphia from 1978 to 1986. He estimates the cross-price elasticity of transit ridership with respect to variable automobile operating costs of 1.05 in the short-run and 2.69 in the long-run.

The last three studies listed are of particular interest for two reasons: first, the purpose of all three studies is to specifically model the impact of gasoline price on transit demand as opposed to simply including it alongside several other variables and second, they analyze recent data, making their estimates more helpful in understanding the role gasoline may play in explaining the recent trends in travel behavior. Currie and Phung (2007) analyze aggregate US ridership data by mode from the American Public Transportation Association (APTA), a trade organization consisting of a majority of US public transit agencies. For all modes, they find a total cross-elasticity of .12, and by mode they estimate cross-price elasticities of .33 for light rail, .17 for heavy rail, and .04 for bus. They also interact various world events with this cross-price elasticity to see if the effect of gasoline prices on transit ridership has changed over time. They find that allowing 9/11, the Iraq War, and Hurricane Katrina to interact with cross-price elasticity increased the model's R^2; the elasticity estimates all increased after 9/11 and decreased after the Iraq War and Katrina with only one exception (the elasticity of commuter rail demand with respect to gasoline price increased .01 after Iraq). Although an interesting finding, the magnitude of these shifts is quite small, often only .01, and they offer no explanation regarding the forces behind the shifts.

Haire and Machemehl (2007) also use data from the APTA to estimate cross-price elasticities for five large U.S. cities, Atlanta, Dallas, Los Angeles, San Francisco, and Washington DC, from 1999 to 2006. Their results are summarized in Table 2.2.

Table 2.2 Empirical Relationships between Fuel Price and Transit Demand (From Haire and Machemehl 2007)

Mode	City	Estimate
Motorbus	Dallas	0.5404
	Washington, DC	0.3097
	Los Angeles	0.2229
Light rail	Dallas	0.1058
	Los Angeles	0.0582
Heavy Rail	Washington, DC	0.4043
	Los Angeles	0.1053
	San Francisco	0.2270
Commuter Rail	Dallas	0.4923
	Los Angeles	0.2131
	San Francisco	0.3735

Note: All estimates are significant at the 10% level.

As is evident in Table 2.2, their estimates vary widely from city to city and between modes. In addition to the significant results listed in Table 2.2, they found that motorbus ridership in Atlanta and San Francisco, heavy rail ridership in Atlanta, and commuter rail ridership in Washington, DC were not significantly correlated with fuel prices. On average, they find a 1% increase in fuel price leads to a .24% increase in transit ridership, and by transit mode, the cross-elasticities were estimated to be .24 for bus, .07 for light rail, and .27 for both heavy and commuter rail.

Jeremy Mattson (2008) uses APTA data to analyze aggregate bus ridership from 1999 through 2006. He estimates the cross-price elasticity to be 0.123 for cities with more than two million residents, 0.128 for cities with a one-half to two million residents, 0.164 for cities with 100,000 to 500,000 residents, and .081 for cities with less than 100,000 residents. He does not explain why this estimate might vary by population. Next, he uses data from the National Transit Database (NTD) to analyze the impact of gasoline prices on bus ridership in eleven small cities in the Midwest and Mountain region from 1997 to 2006. For the individual cities, he finds cross-price elasticities ranging from .08 to .50, but when he combines all the cities into a yearly panel dataset, he estimates an average gasoline cross-price elasticity of .12.

While these three papers offer some insight into the effect of gasoline price on transit demand, each has a significant limitation. First, in just looking at aggregate data, Currie and Phung ignore the wide differences that exist between cities. As travel mode choices are highly dependant on a particular location and service offerings, an aggregate study does not offer insight into where and why people are riding transit more. In only looking at several similar cities, Haire and Machemehl and Mattson both fail to provide much context for their results. Haire and Machemehl's results are only applicable to the five cities they study, whereas Mattson's results have little meaning outside the small towns in the Midwest that he studies. In addition to including the most recent data available, my study will incorporate data from 218 cities nationwide. This will ensure that my estimated cross-price elasticities by mode have accounted for the city-specific factors that largely determine the estimates and my result will also allow any single city's elasticity to be compared to similar cities across the nation. The literature utilizes many different specifications and explanatory variables. The next section addresses these differences and develops a model to estimate the impact of gasoline price in many US cities.

3. Developing a Model

3.1 Models Used in the Literature

Applying consumer theory to public transportation, Berechman (1993) prescribes a generalized demand function **D = D (P, T, Y, Q, I, V, Z)** where D is transit demand in trips, P is fare, T is a vector of travel times, Y is a vector of service provision, Q is a vector of service qualities, I is a vector of population characteristics, V is a vector of substitute prices, and Z is a vector of urban characteristics. All of the previously cited time-series studies build off this framework, but as shown in Table 3.1 below, each uses a unique combination of functional form and explanatory variables.

Table 3.1 Models from Previous Studies of the Impact of Gas Prices on Transit Demand

Study	Specification	Dynamic?	Observations	Explanatory Variables	Dummy Variables
Agthe and Billings 1978	log-log	no	monthly	supply	Energy crisis, summer
Wang and Skinner 1984	linear & log-log	no	monthly	fare, supply	# working days
Doi and Allen 1986	linear & log-log	no	monthly	fare, bridge toll	summer, October,
Voith 1997	linear	Geometric lags	yearly	supply, fare, local pop.	Station FE's,
Dargay and Hanly 2001	log-log	Partial adjustment	yearly	income, supply, motoring costs	Allow cross-elasticity to vary by county

3.2 Empirical Considerations

There are two important econometric considerations that can complicate a study of public transit ridership: the lagged impact of determinants, as reflected in the difference between short-run and long-run elasticities, and simultaneity between supply and demand. Regarding the lagged effect of changes in explanatory variables, Goodwin (1992) notes that it is known that it takes time for demand to respond to changes in gasoline prices, therefore a demand model must include lagged gasoline prices or it will suffer a specification bias. Chen (1997) presents several methods of lagging explanatory variables with the aim of reducing multicollinearity. While it is true that multicollinearity makes it difficult to determine the effect of a particular lag, when added, the lags will sum to the total effect of a permanent change in gasoline price.

Simultaneity arises when supply is incorporated as an explanatory variable. As supply is a function of past demand, which is correlated with current demand, including supply can bias a model's estimates. The size of the simultaneity effect is not certain, but the direction is known to bias supply upwards and other explanatory variables downward. Wang and Skinner (1984) argue that using monthly data alleviates much of the simultaneity bias, as transit supply is determined on a yearly basis. A panel data study of a Philadelphia transit agency by Voith (1991) instruments for transit supply using information about the transit authority's subsidies, costs, and lagged deficits to perform a 2SLS estimation. The 2SLS model produces significantly different results than his OLS estimation but the difference is small. However, a similar procedure is very difficult for studies of multiple cities where similar operating data is not available. As there are no reliable instruments that could be used for cities across the nation, I am forced to use monthly data and will have to simply address the fact that my results are likely to be slightly biased.

3.3 Specification

To allow the coefficients to represent elasticities and for ease of comparison with the literature, I will estimate a log-log demand specification for each mode of transit. In addition to including transit ridership as the dependent variable and gasoline price as the explanatory variable, several factors need to be accounted for. First, despite the aforementioned possibility of simultaneity bias, a measure of transit supply is included to account for the general trend towards increased transit supply, as well as account for any service shocks that result from occurrences such as strikes or the construction of a new transit lines. Also, including transit supply controls for the number of working days in a given month, as both supply and ridership are higher on working days than on weekends. Second, ridership level and gasoline prices both increase every year over the range of observations. Including yearly fixed effects (Y_{ij}) will account for unobserved determinants of transit demand that vary year over year, such as fare level, service quality, and economic and demographic factors. Finally, as seen in Figures 3.1 and 3.2, both gasoline and transit ridership exhibit strong seasonality. To address this, monthly fixed effects (M_{ik}) will be included in the model. Since yearly unobservable factors and seasonality vary dramatically between cities, it would be naïve to apply similar monthly fixed effects to ridership demand equations for very different cities, for instance Chicago and Miami. The specification will therefore include different yearly and monthly fixed effects for each city. Including the previously mentioned variables, the resulting specification is:

$$\ln R_{it} = \alpha_0 + \alpha_1 \ln S_{it} + \alpha_2 \ln P_{it} + \Sigma\beta_{ij} Y_j + \Sigma\beta_{ik} M_k + \varepsilon_{it} \qquad \text{(I)}$$

where R is ridership, S is transit supply, P is average regional gasoline price, Y are yearly fixed effects, M are monthly fixed effects, and ε is a mean-zero error term. The subscripts i, t, j, and, k indicate the city, observation period, year, and month, respectively. The next specification is identical to Equation (I) but includes six months of lagged gasoline prices. While "short-run" effects are generally considered to last up to a full year after a price change, the purpose of these lags is to gauge whether they significantly add explanatory power to the model or if they produce drastically different results than the previous specification.

$$\ln R_{it} = \alpha_0 + \alpha_1 \ln S_{it} + \alpha_2 \ln P_{it} + \alpha_3 \ln P_{it-1} + \ldots + \alpha_8 \ln P_{it-6} + \Sigma\beta_{ij} Y_j + \Sigma\beta_{ik} M_k + \varepsilon_{it} \quad \text{(II)}$$

Next, to assess how the impact of gasoline prices on transit ridership differs between cities, Equation (I) will be estimated separately for commuter, heavy, and light rail modes in every city with rail transit. For motorbus, instead of estimating each city individually, the 218 cities will be divided into four groups based on 2007 metropolitan population as reported by the US Census Bureau. These four population groups are: greater than 2 million people, between .5 and 2 million people, between 100,000 and 500,000 people, and less than 100,000 people. The following specification will be estimated for each of these four population categories which allow monthly and yearly fixed effects to vary by city, like equations I and II, but only estimates one cross-price elasticity for each population group (p).

$$\ln R_{it} = \alpha_{0p} + \alpha_{1p} \ln P_{it} + \alpha_{2p} \ln S_{it} + \Sigma\beta_{ij} Y_j + \Sigma\beta_{ik} M_k + \varepsilon_{it} \quad \text{(III)}$$

Finally, I will allow gasoline price to interact with the yearly dummy variables to measure how the effect of gasoline prices on transit ridership changes over time. Again, different coefficients on the monthly dummy variables will be estimated for each region.

$$\ln R_{it} = \alpha_0 + \Sigma\alpha_{1j} Y_j * \ln P_{it} + \alpha_2 \ln S_{it} + \Sigma\beta_{ij} Y_j + \Sigma\beta_{ik} M_k + \varepsilon_{it} \qquad \text{(IV)}$$

3.4 Predicted Results

In all specifications, the coefficients on transit supply and gasoline price are expected to have positive values. In general, the coefficient on transit supply is expected to be greater than the coefficient on gasoline price. The coefficient on gasoline price is likely to vary between modes and cities but should stay between 0 and 1, as transit demand is generally inelastic. I hypothesize that the coefficient on gasoline price will increase over time, as higher gasoline prices and related media attention cause people to become more aware of their gasoline expenditures. As commuter rail and light rail serve a greater percentage of discretionary riders[5], I would expect these modes to show the greatest increase in cross-price elasticity as gasoline price rises.

[5] Discretionary riders refer to mass transit patrons who possess a private vehicle. Dependent riders are individuals without a private vehicle that rely on mass transit for transportation.

4. Panel Data Analysis

4.1 Data

The transit ridership and supply data are taken from the National Transit Database (NTD). The federal government requires all transit agencies receiving funding from the Federal Transit Administration to submit ridership and supply data to the NTD. This study uses monthly NTD data from January 2002 through August 2008, 80 periods in total. After removing data containing multiple discontinuous sections, the panel dataset includes 218 metropolitan areas, of which all 218 have motorbus transit, 13 have commuter rail, 11 have heavy rail, and 17 have light rail. The ridership data is measured in unlinked passenger trips (UPT), which are the number of "legs" of journeys taken in a given month. There are two concerns with UPT. First, technological advances have made them easier to accurately measure, and second, they overcount multi-trip journeys. If increases in technology allow better measurement of UPT, the data could reflect an increase in measurement rather without a true underlying increase in ridership. However, by 2002, advanced measurement technology was already widely used, so this is not a serious concern. Similarly, a trend in transit pricing towards a flat fee is likely to have encouraged multiple leg journeys, meaning the inherent overcounting associated with UPT could lead to artificially inflated growth in ridership (FitzRoy and Smith, 1999). Polzin and Chu (2006) note that UPT is the only measure of transit demand available, and suggest that its drawbacks should not overshadow the fact that it proxies for true demand very well. The transit supply data is reported in vehicle revenue miles (VRM), which are the total number of miles all transit vehicles cover while in service over a given period.

Table 4.1 below provides a breakdown of the ridership data by mode and table 4.2 contains the average distribution of ridership in cities with multiple modes of transit.

The gasoline price data is provided by the US Energy Information Administration (EIA). The figures are average prices for all grades of gasoline sold in each of seven regions nationwide and are reported in nominal dollars. I convert these prices to real 2000 US dollars using GDP implicit price deflators.

Figures 4.1 and 4.2 show how the twelve-month moving averages of vehicle miles traveled and public ridership have varied alongside the twelve month average of real gasoline prices since 2002. The VMT are measured in billions of miles driven and in 2007, the 12-month moving average VMT declined for the first time since the Federal Highway Administration began recording the figure in 1946. The ridership figures are measured in thousands of Unlinked Passenger Trips. The gasoline prices have been adjusted for inflation and are reported in 2000 USD. Figure 4.3 shows the each month's average gasoline price relative to the yearly average, and Figure 4.4 shows each month's average total transit ridership level relative to the yearly average.

Table 4.1 Ridership by mode	% ridership	# cities
Commuter Rail	4.88%	13
Heavy Rail	36.47%	11
Light Rail	4.06%	17
Motorbus	54.58%	218

Table 4.2 Ridership in cities w/ rail	# cities	% Bus	% CR	% HR	% LR
Bus & Commuter Rail	1	97.8	2.2		
Bus & Heavy Rail	1	49.4		50.6	
Bus & Light Rail	8	80.7			19.3
Bus, Commuter, & Heavy Rail	4	69.9	3.4	26.7	
Bus, Heavy & Light Rail	1	99.8		0.1	0.1
Bus, Commuter, & Light Rail	2	68.5	1.3		30.2
Bus, Commuter, Heavy & Light Rail	6	54.8	5.9	25.8	13.5

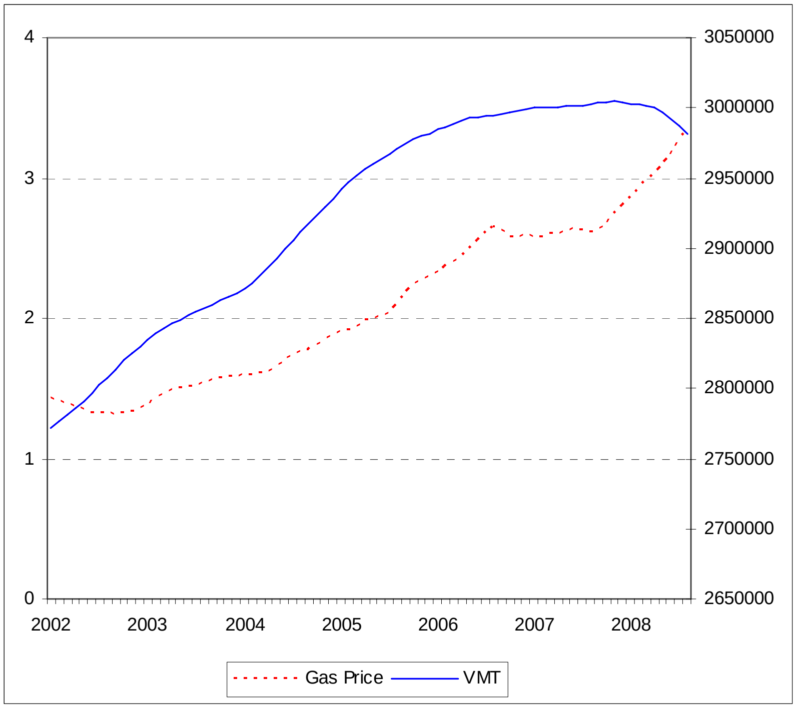

Figure 4.1 Avg. Vehicle Miles Traveled and Avg. Gas Price, 2002 to 2008

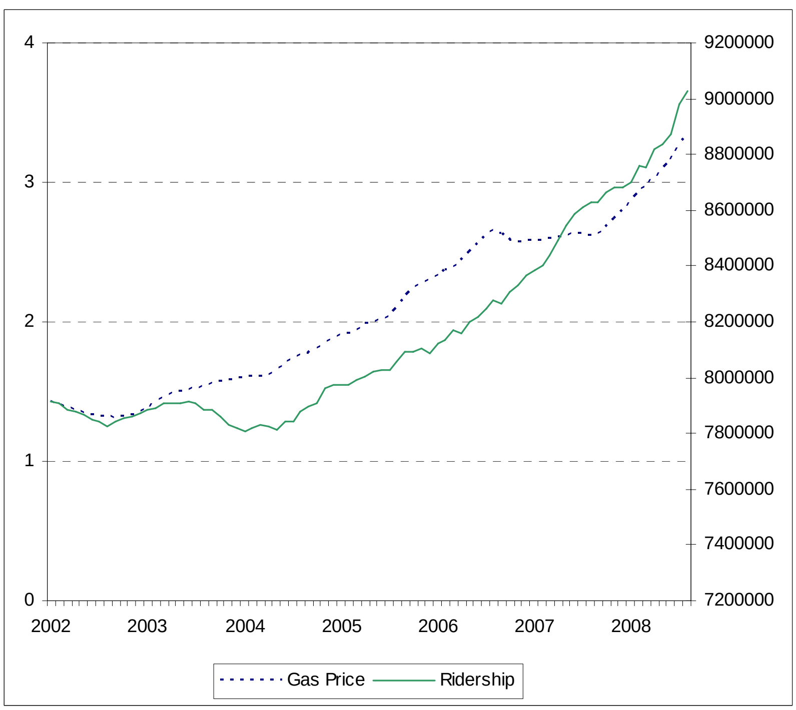

Figure 4.2 Avg. Aggregate Transit Ridership and Avg. Gas Price, 2002 to 2008

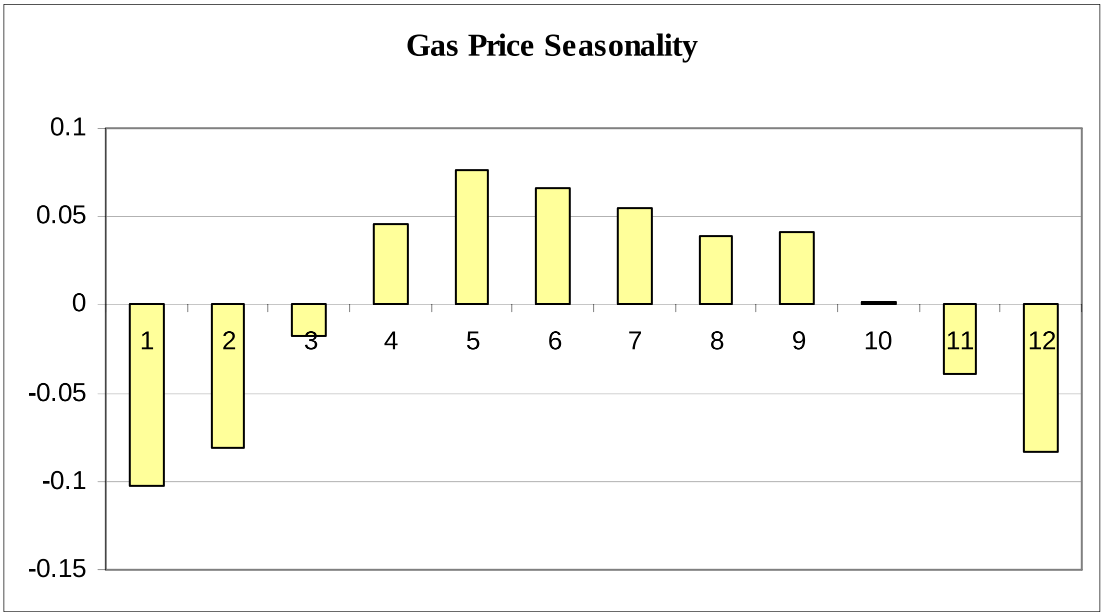

Figure 4.3 Monthly US gasoline prices relative to 12 month moving average

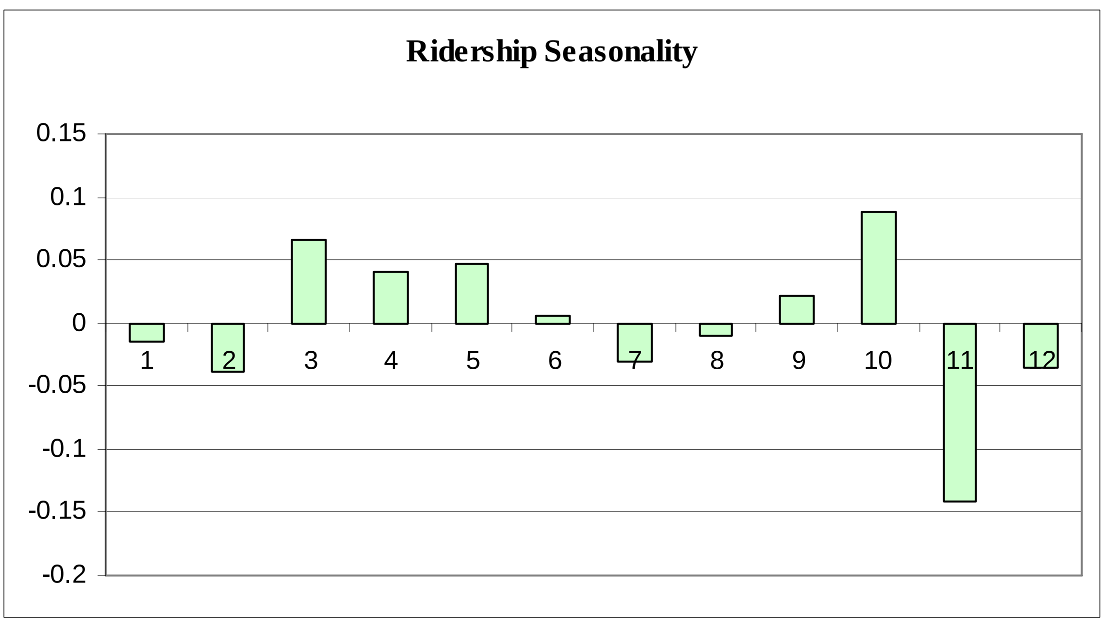

Figure 4.4 Monthly total US transit ridership relative to 12 month moving average

4.2 Results

Table 4.3 Results of Equations I and II, all modes

	I		II	
Commuter Rail	coefficient	t-value	coefficient	t-value
supply	0.290	13.83**	0.272	12.20
gas price	0.087	3.51**	0.019	0.47
$(\text{gas price})_{n-1}$			0.129	2.23**
$(\text{gas price})_{n-2}$			-0.037	-0.56
$(\text{gas price})_{n-3}$			0.066	0.99
$(\text{gas price})_{n-4}$			-0.070	-1.04
$(\text{gas price})_{n-5}$			0.103	1.77*
$(\text{gas price})_{n-6}$			-0.004	-0.10
∑ (gas price)			0.206	
intercept	9.124	31.68**	8.784	20.17**
R^2	*0.937*		*0.937*	
Heavy Rail	coeff.	t-value	coeff.	t-value
supply	0.175	8.61**	0.687	20.18**
gas price	-0.012	-0.33	-0.017	-0.35
$(\text{gas price})_{n-1}$			0.082	1.17
$(\text{gas price})_{n-2}$			-0.143	-1.81*
$(\text{gas price})_{n-3}$			0.082	1.04
$(\text{gas price})_{n-4}$			0.027	0.34
$(\text{gas price})_{n-5}$			0.004	0.06
$(\text{gas price})_{n-6}$			-0.014	-0.29
∑ (gas price)			0.022	
intercept	13.119	38.86**	5.589	9.14**
R^2	*0.781*		*0.859*	
Light Rail	coeff.	t-value	coeff.	t-value
supply	0.592	19.14**	0.581	16.99**
gas price	0.100	2.82**	0.133	2.32**
$(\text{gas price})_{n-1}$			0.020	0.23
$(\text{gas price})_{n-2}$			0.004	0.04
$(\text{gas price})_{n-3}$			0.083	0.87
$(\text{gas price})_{n-4}$			0.051	0.53
$(\text{gas price})_{n-5}$			0.095	1.14
$(\text{gas price})_{n-6}$			0.017	0.29
∑ (gas price)			0.403	
intercept	6.055	14.26**	4.733	7.27**
R^2	*0.883*		*0.885*	

Table 4.3, cont. Results of Equations I and II, all modes

Motorbus	coefficient	t-value	coefficient	t-value
supply	0.410	32.61**	0.413	32.01**
gas price	0.063	1.450	0.007	0.11
$(\text{gas price})_{n-1}$			0.118	1.20
$(\text{gas price})_{n-2}$			-0.061	-0.55
$(\text{gas price})_{n-3}$			-0.008	-0.07
$(\text{gas price})_{n-4}$			0.027	0.24
$(\text{gas price})_{n-5}$			0.044	0.45
$(\text{gas price})_{n-6}$			-0.004	-0.05
$\sum$ (gas price)			0.124	
intercept	7.003	27.13**	6.657	12.04
R^2	*0.167*		*0.165*	

Notes:

Regressing Equation (I) produces cross-price elasticity values with respect to gasoline price of 0.087 for commuter rail, -0.012 for heavy rail, 0.100 for light rail, and 0.063 for motorbus, but only for commuter rail and light rail are these values significant at the 10% level. These estimates are lower than those reported in the literature and indicate that gasoline price and ridership are not very strongly correlated over the entire range of observations for heavy rail and motorbus. In each regression, the supply variable was significant at the 1% level, and the yearly and monthly fixed effects were both jointly significant in each model. Equation (II) included six months of lagged gasoline prices. Regressing this specification was meant to help determine if transit demand is quickly adjusting to changes in gasoline price or if there is a significant delayed effect. The high degree of collinearity between the lagged gasoline prices makes interpreting any specific coefficient impossible and decreases each of their standard errors. When their coefficients are summed, however, they still represent the impact that a change in gasoline price has on transit demand for the first six months. By mode, the sum of these coefficients is 0.206 for commuter rail, 0.022 for heavy rail, 0.403 for light rail, and 0.124 for motorbus.

These values fall much closer to those found in the literature, but the impact of gasoline prices on heavy rail is lower than expected and the effect on light rail is towards the upper range of reported cross-price elasticities. Looking closer, including the lagged gasoline prices only significantly increased the R^2 for heavy rail and actually decreased the R^2 of motorbus. This suggests that they did not add explanatory power to the model and thus the cross-price elasticity estimates produced by adding their coefficients are not very meaningful.

Table 4.4 Cross-Price Elasticity Estimates by City, Commuter Rail

metro area	gas price ε	t-value	R^2	2007 population
New York	0.024	0.79	0.941	18,815,988
Los Angeles	**0.126**	**2.29****	0.956	12,875,587
Chicago	0.036	0.74	0.867	7,952,540
Philadelphia	**0.131**	**3.01****	0.977	6,145,037
Miami	0.021	0.13	0.801	5,827,962
Dallas - Fort Worth	**0.213**	**2.25****	0.812	5,413,212
Boston'	-0.012	-0.310	0.876	5,306,565
Washington, DC	-0.077	-1.31	0.911	4,482,857
San Francisco	0.098	1.31	0.956	4,203,898
Seattle	0.088	0.77	0.989	2,974,859
San Diego	**0.204**	**2.00****	0.904	2,668,056
Baltimore	-0.009	-0.13	0.908	2,536,182
Hartford	0.110	1.12	0.894	1,189,113

Notes: VRM, monthly fixed effects, and yearly fixed effects were included in each specification. n = 10 cities. *, ** = 10%, 5% significance.

Table 4.5 Cross-Price Elasticity Estimates by City, Heavy Rail

metro area	gas price ε	t-value	R^2	2007 population
New York	-0.008	-0.200	0.934	18,815,988
Los Angeles	0.011	0.060	0.897	12,875,587
Chicago	**0.091**	**2.08****	0.923	7,952,540
Philadelphia	-0.025	-0.440	0.924	5,827,962
Miami	-0.126	-1.560	0.853	5,413,212
Washington, DC	0.016	0.350	0.943	5,306,565
Atlanta	-0.092	-1.160	0.840	5,278,904
Boston'	**0.137**	**2.01****	0.860	4,482,857
San Francisco	**0.099**	**1.97***	0.934	4,203,898
Baltimore	0.003	0.080	0.891	2,668,056
Cleveland	**-0.377**	**-2.23****	0.852	2,096,471

Notes: VRM, monthly fixed effects, and yearly fixed effects were included in each specification. n = 10 cities. *, ** = 10%, 5% significance.

Table 4.6 Cross-Price Elasticity Estimates by City, Light Rail

metro area	gas price ε	t-value	R2	2007 population
New York	-0.056	-0.83	0.992	18,815,988
Los Angeles	0.071	0.45	0.907	12,875,587
Dallas - Fort Worth	0.114	1.61	0.907	6,145,037
Philadelphia	-0.071	-0.77	0.966	5,827,962
Boston	0.116	1.24	0.825	4,482,857
San Francisco	0.152	1.29	0.636	4,203,898
San Diego	-0.081	-0.61	0.931	2,974,859
St. Louis	0.062	0.32	0.898	2,803,707
Baltimore	0.054	0.38	0.839	2,668,056
Denver	**0.507**	**3.16****	0.940	2,464,866
Pittsburgh	0.047	0.50	0.651	2,355,712
Portland, OR	**0.212**	**2.84****	0.939	2,175,113
Cleveland	-0.103	-0.42	0.648	2,096,471
Sacramento	0.099	0.73	0.915	2,091,120
San Jose	**0.229**	**1.93***	0.957	1,803,643
Buffalo	0.138	0.87	0.490	1,128,183
Salt Lake City	0.211	1.03	0.749	1,099,973

Notes: VRM, monthly fixed effects, and yearly fixed effects were included in each specification. n = 10 cities. *, ** = 10%, 5% significance.

The results of estimating Equation (I) for individual cities for the three rail modes are presented in Tables 4.3 through 4.6. For commuter rail, VRM and monthly fixed effects were jointly significant for each city. Yearly fixed effects were jointly significant for each city except Boston, but were included in each city's specification as they increased the regression's R^2. Four of thirteen cities displayed a positive, significant coefficient on gas price which had an average coefficient on gas price of 0.168. For heavy rail, four of eleven cities had a significant coefficient on gasoline price. Chicago, Boston, and San Francisco displayed positive cross-price elasticities in the range of 0.091 to 0.137, but Cleveland's cross-price elasticity of demand was estimated as -0.377. This highly significant, large negative coefficient in counterintuitive and suggests that something unusual occurred with Cleveland's transit system from 2002 to 2008. For light rail, three of seventeen cities had significant coefficients on gasoline price. The largest was Denver, which had a cross-price elasticity of 0.507. In each of these tables, each city's 2007 metropolitan population is reported. This was intended to be used to determine if the size or significance of the coefficients on gas price was correlated with population. However, so few cities had significant findings that such an exercise would not produce a meaningful result.

Table 4.7 Cross-Price Elasticity Estimates by Population, motorbus

metro population	coefficient	t-value	R^2	n
>2 mil.	**0.092**	**3.14***	0.581	19
500k - 2 mil	**0.082**	**2.85***	0.319	48
100k - 500k	0.053	1.03	0.307	100
< 100k	0.047	0.32	0.233	51

* = 5% significance.

Table 4.7 reports the estimated cross-price elasticities of bus transit for four groups of cities, categorized by metropolitan population. Cities with more than 2 million people and between .5 million and 2 million people had significant cross-price elasticity estimates of .092 and .082, respectively. The two smaller categories did not have significant cross-price elasticities.

Table 4.8 Results of Equation (IV)

	Commuter Rail		Heavy Rail		Light Rail		Motorbus	
	coeff.	t-value	coeff.	t-value	coeff.	t-value	coeff.	t-value
2002*gasprice	0.003	0.05	**-0.153**	**-1.88***	0.115	1.48	-0.042	0.003
2003*gasprice	-0.042	-0.53	0.143	1.11	-0.029	-0.26	0.051	-0.042
2004*gasprice	-0.031	-0.50	-0.044	-0.46	0.108	1.21	-0.020	-0.031
2005*gasprice	**0.070**	**1.89***	0.013	0.23	**0.121**	**2.28****	0.089	**0.070**
2006*gasprice	**0.102**	**2.51****	-0.073	-1.2	0.011	0.19	0.023	**0.102**
2007*gasprice	**0.083**	**1.75***	-0.003	-0.04	**0.159**	**2.42****	0.048	**0.083**
2008*gasprice	**0.316**	**6.15****	0.084	1.07	**0.284**	**3.84****	**0.221**	**0.316**
R^2	*0.9395*		*0.7842*		*0.8846*		*0.1674*	

Table 4.8 contains the yearly estimates of cross-price elasticity for each mode from 2002 to 2008. For commuter rail, light rail, and motorbus, the cross-price elasticity estimates increase in both magnitude and significance over time. Figures 4.5 through 4.8 show these estimates over time, including 90% confidence bands to indicate which estimates were significantly different from zero. For commuter rail and light rail, this change is particularly striking. All the previous regression results had found that from 2002 to 2008, gasoline prices were not consistently a significant determinant of transit demand. These results help explain that finding. It appears that for the first few years of the period of observation, when gas prices were quite low, there was not a strong relationship between gasoline prices and transit demand. It was only later, in 2007 and 2008, that the effect of gasoline prices became significant and increasingly large.

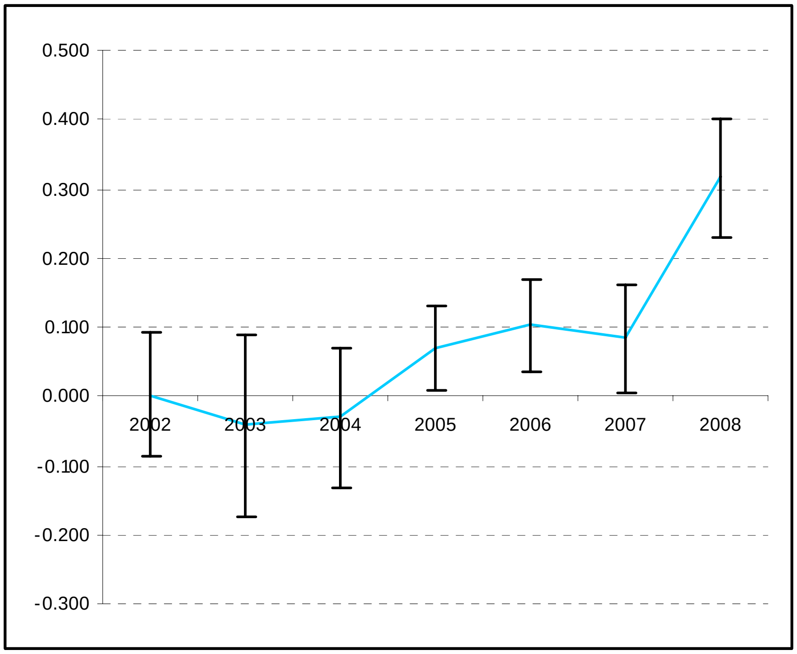

Figure 3.1 Cross-price elasticity estimates for Commuter Rail, 2002- 2008

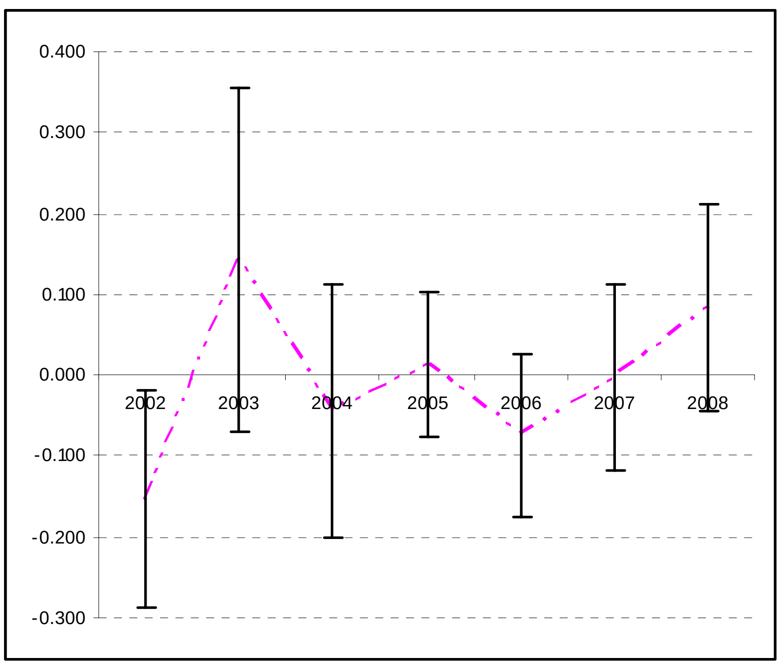

Figure 3.2 Cross-price elasticity estimates for Heavy Rail, 2002- 2008

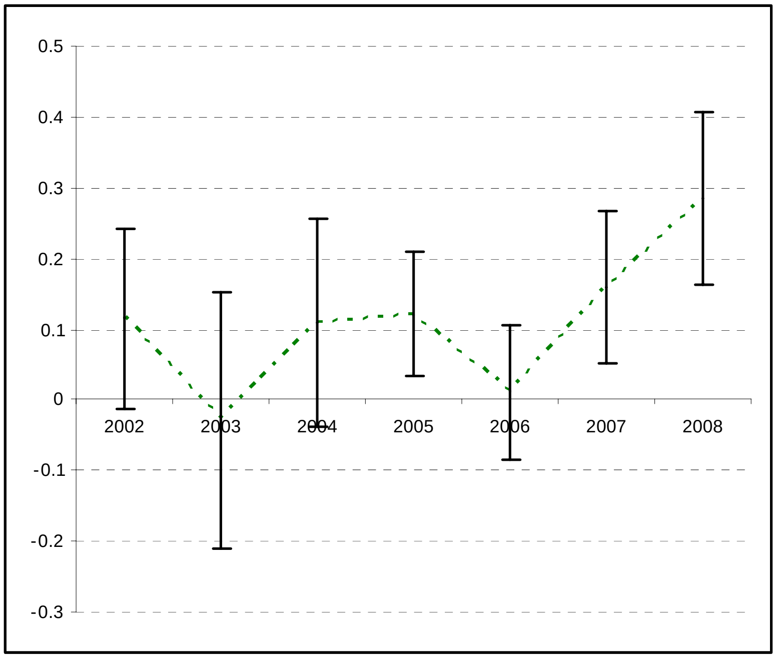

Figure 3.3 Cross-price elasticity estimates for Light Rail, 2002- 2008

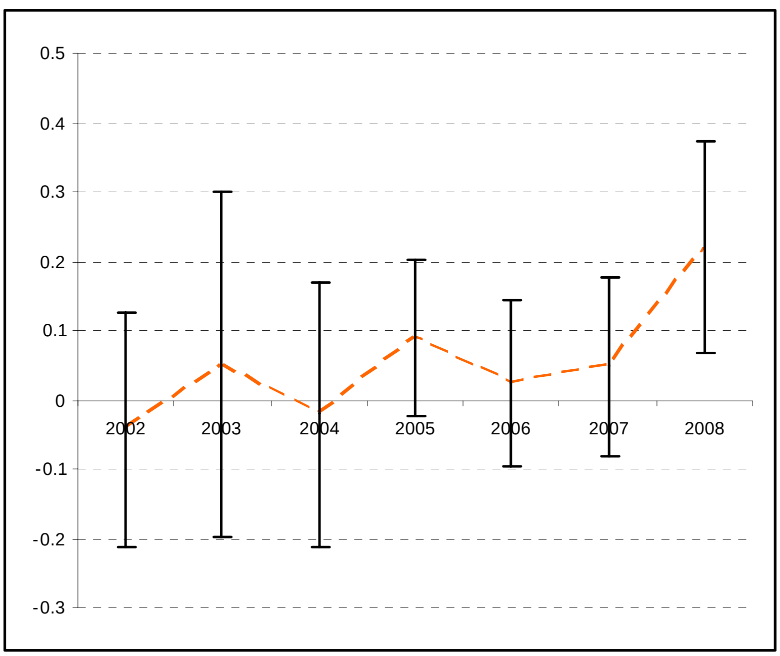

Figure 3.4 Cross-price elasticity estimates for Motorbus, 2002- 2008

5. Conclusion

In agreement with the previous literature, this research finds that the impact of gasoline prices on public transportation demand varies widely from city to city and between modes. On the whole, gasoline prices did not significantly determine transit demand from 2002 to 2008. However, when the cross-price elasticity is broken down into separate yearly estimates, one finds that for commuter rail, light rail, and motorbus, the impact of gasoline price on transit demand became more significant and substantial as gasoline prices increased. Thus, while gasoline prices may not be the main cause of the trend towards increased ridership since 2002, they certainly played a large role in the recent acceleration in transit ridership growth, as a change in gasoline price was found to have the largest impact on transit ridership during the same period that gas prices were increasing the most.

The finding that gasoline prices have an increasing impact on travel behavior as they reach higher levels has an important impact on transit operation and public policy decisions. Transit operators should tailor their demand forecasts depending on the current levels of gasoline price, and during periods of high prices, they should take measures to provide a more elastic supply of transit, as any additional increase in gasoline prices will likely elicit a large increase in ridership. Also, as gasoline prices are expected to trend upwards in the long-term, they should favor capital investments in commuter and light rail over motorbus and heavy rail, when possible. For policy makers, the knowledge that as gasoline prices increase, vehicle owners are more affected by price changes informs taxation policies. When gasoline prices are high, fuel taxes and congestion tolls are more likely to have an impact in curbing vehicle travel.

While these results suggest that transit demand became increasingly sensitive to gasoline prices from 2002 to 2008, this finding is subject to several assumptions. First, this research does not address the substitution effects between modes in a given city. It could be the case that much of the reported variation in transit mode demand is the product of people switching from one mode to the next, and thus the marginal impact of former vehicle travelers is masked. Second, the elasticity estimates presented in this paper do not address the potential simultaneity bias caused by including supply as an explanatory variable. Transit supply has a very significant, positive coefficient in every specification. Potentially, changes in the ability of transit operators to successfully predict transit demand could cause the coefficient on gasoline price to change. For instance, if operators accurately predicted transit demand in 2002 but were inaccurate in 2008, there would be more variation in ridership to be explained by gasoline prices in 2008 and the estimated cross-price elasticity would be larger, even if the actual impact of fuel prices on consumer behavior was constant. Finally, the estimates of cross-price elasticity by year did not allow gasoline price to have a lagged impact on ridership. While this is expected to bias the coefficients on gasoline price downwards, it could be the case that this bias is not uniform. As gasoline prices rose to unprecedented levels, it could be the case that people simply reacted more quickly.

The relationship between gasoline prices and transit demand is likely to become an increasingly important issue as oil supply drops and global warming and congestion become more severe. There are several extensions to this research that are necessary to better understand how individuals react to gasoline prices. First, as gasoline prices retreated during the second half of 2008, transit ridership levels continued to rise. While this would indicate a weak or even negative relationship between gasoline prices and transit demand, detailed research, especially at the household level, might explain who is riding public transportation and what is motivating them. It is likely that the combined pressure of a struggling economy and high gasoline prices caused people to try using transit and in doing so overcome the initial cost of learning how to use it. Another important line of research will be to research the long-term impacts of sustained high gasoline prices. In the short-run, higher gasoline prices force people to adjust their travel behavior given their current situation, but in the long-term they can change things such as their location of residence and employment and motor vehicle stock and businesses can take measures to facilitate efficient gasoline use. It will be interesting to see where people put their energy in responding to increased gasoline prices and what the effect will be on vehicle demand, suburbanization, urban renewal, and both transit and highway infrastructure development.

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