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by Jeremy Mattson

This study estimates the effects of gas prices on bus ridership for different types of transit systems. Because the price of gas can have a delayed effect on the demand for transit, a dynamic polynomial distributed lag model is utilized which measures short- and longer-run effects. The model is first applied to aggregate data for cities of different sizes and then to three specific small urban and rural transit systems in the Upper Great Plains. The results show that bus ridership is fairly inelastic with respect to gasoline price. Most of the estimated elasticities are in the range of 0.08 to 0.22, with two estimates being as high as 0.5.

INTRODUCTION

Rising fuel prices the last few years have led to significant increases in costs for public transit agencies. A possible benefit from higher gas prices, though, is an increase in transit ridership. As the cost of fueling a car increases, people may seek ways to reduce fuel consumption, and one such option is public transportation. A number of news reports across the United States have indicated that transit ridership has increased with the rise in gas prices, but few studies have been conducted to confirm this relationship or measure the extent of it. A significant increase in fare revenue resulting from increased ridership would allow transit agencies to continue operating without making substantial changes. But if fare revenues do not increase sufficiently, transit agencies may need to investigate an increase in fares, a decrease in service, or they may need to seek additional public funding.

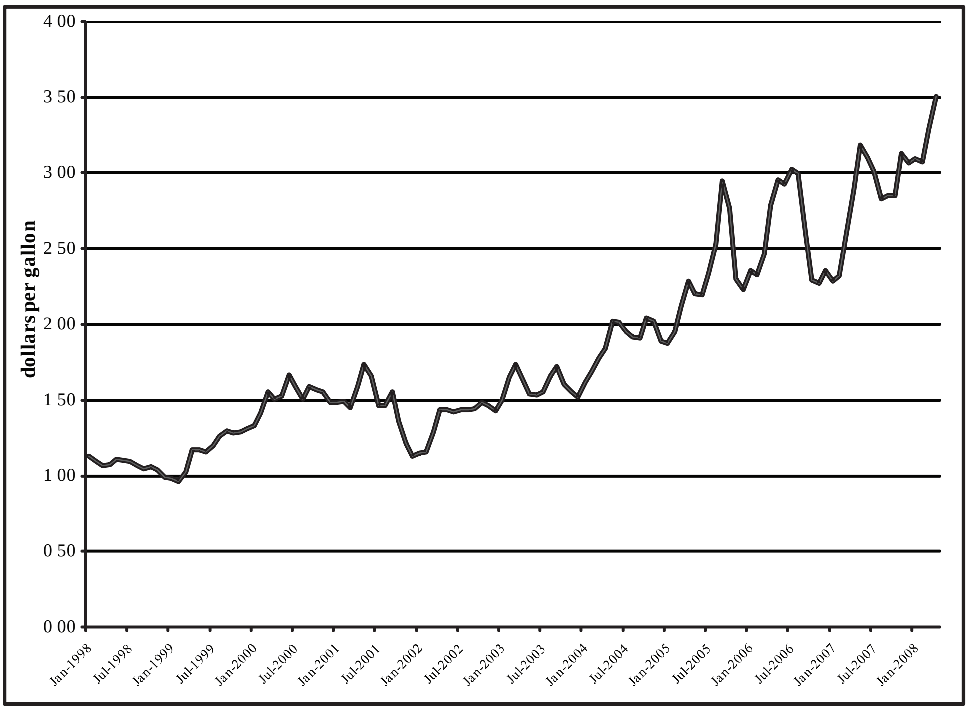
The objective of this study is to estimate the effect of gas prices on bus ridership for different types of transit systems. A secondary objective is to examine short-run versus longer-run impacts. It is possible that gas prices may not affect ridership in the same way for all transit agencies. Transit buses that operate longer routes could be affected differently than those that operate shorter routes, as someone who travels longer distances will likely be more sensitive to changes in gas prices, and individuals in larger cities may respond differently to changes in gas prices than those who live in smaller cities or rural areas. Previous research has shown that consumer response to fare changes vary by size of city (Litman 2004, Paulley et al. 2006), but similar research has not been conducted regarding gas prices. Studies in Australia have suggested that ridership on longer routes is more sensitive to changing gas prices (Wallis and Schmidt 2003, Currie and Phung 2008). If there is any effect on ridership, it would be interesting to examine both the short- and long-run impacts. There may be a lagged effect as individuals may be slow to respond to the rising prices. Alternatively, a sudden large price increase could lead to a jump in transit ridership that is not sustained in the long run if riders return to their automobiles.

This article examines the recent trends in transit ridership and gas prices and develops an econometric model to estimate the relationship between these two variables. Because the price of gas can have a lagged effect on demand for transit, a dynamic model that estimates both short- and long-run elasticities is more appropriate than a static model. To this end, a polynomial distributed lag model, also known as the Almon model, is used. This model is applied first to aggregate U.S. bus ridership for cities of different sizes, using data from the American Public Transportation Association (APTA). Ridership is then estimated for three specific transit agencies: Fargo-Moorhead Metro Area Transit, Clay County Rural Transit, and the Cheyenne Transit Program. These agencies represent small urban and rural systems in North Dakota, Minnesota, and Wyoming. A model is developed and estimated for each system, and the effects of gas prices on ridership are discussed. The results of this study are important because they provide some insight on the ability of transit agencies to survive under rising fuel costs.

RECENT TRENDS IN TRANSIT RIDERSHIP AND GAS PRICES

Gas prices have roughly tripled over the last decade. After being relatively stable for much of the 1990s, the average price of a gallon of gas in the United States rose from $1.35 in 2002 to $2.81 in 2007 (Figure 1). Even in inflation-adjusted terms, the price of gas increased by about 80% from 2002 to 2007. It may be expected that such a significant rise in the price of gasoline may affect travel behavior. In fact, a number of transit systems have seen an increase in ridership in recent years and numerous press reports have suggested that the rise in gas prices is one of the primary causes for this increase in passengers.

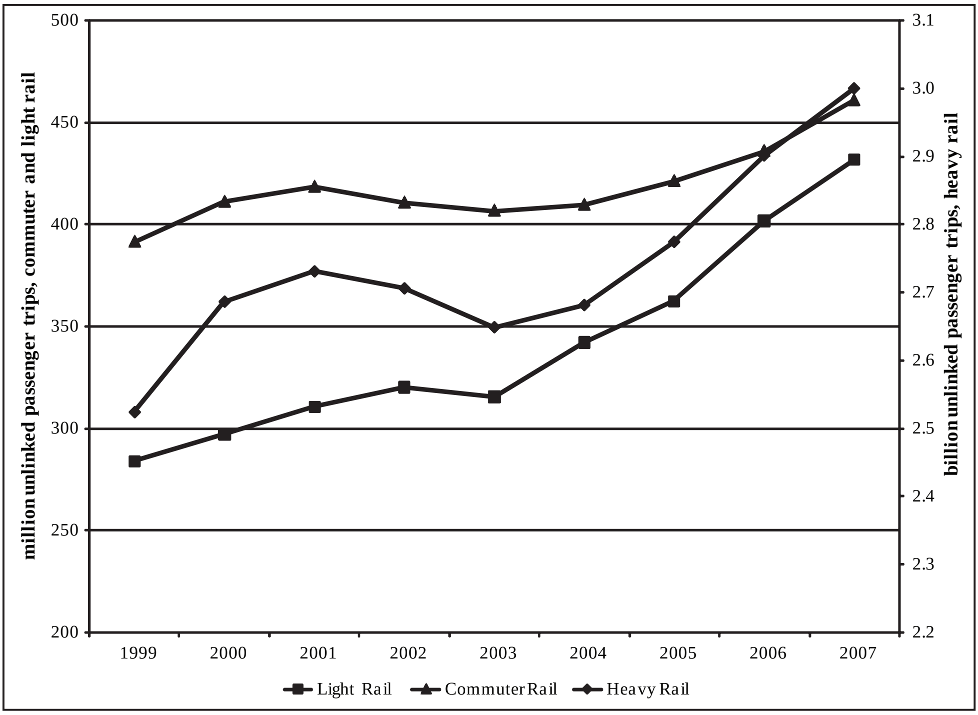
Figure 1: U.S. Average Gasoline Price



Source: Energy Information Administration, U.S. Department of Energy

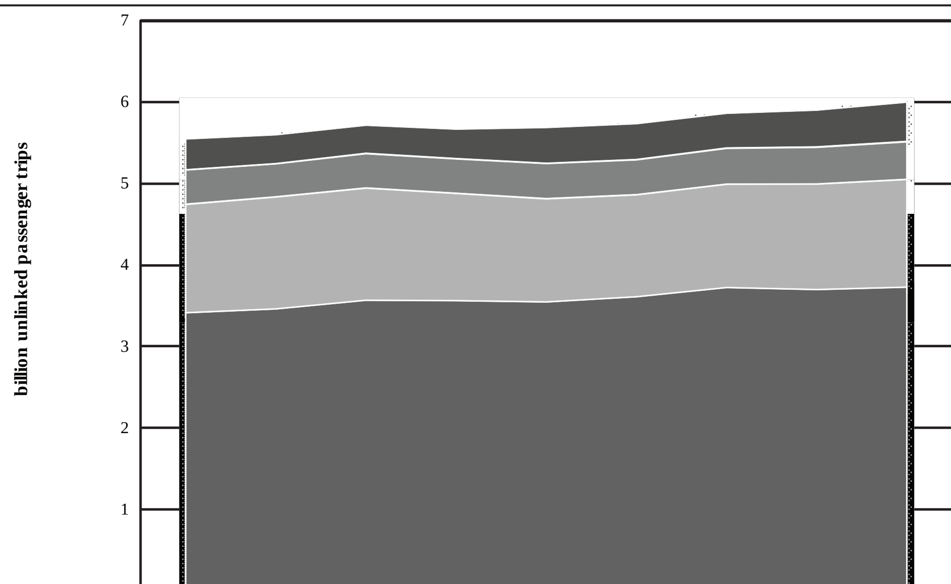
Meanwhile, transit ridership in the United States has been consistently growing over the last several years (Figures 2 and 3). Heavy rail ridership increased from 2.5 billion unlinked passenger trips in 1999 to 3.0 billion in 2007, an annual increase of 2.2%. Light rail has had the highest rate of growth, rising 5.4% annually from 284 million to 432 million unlinked passenger trips per year over the 1999 to 2007 period. Commuter rail ridership, meanwhile, grew from 392 million to 461 million trips per year over the same period, an annual growth rate of 2.1%.

Figure 2: U.S. Rail Transit Ridership, 1999-2007



Source: American Public Transportation Association

Figure 3: U.S. Bus Transit Ridership by City Population Groups, 1999-2007



	1999	2000	2001	2002	2003	2004	2005	2006	2007
Below 100,000	0.38	0.35	0.34	0.36	0.44	0.44	0.42	0.45	0.48
100,000-499,999	0.42	0.41	0.42	0.42	0.43	0.43	0.44	0.45	0.46
500,000-1,999,999	1.33	1.37	1.38	1.32	1.27	1.25	1.27	1.30	1.32
2,000,000+	3.42	3.47	3.58	3.57	3.56	3.62	3.73	3.71	3.74

Source: American Public Transportation Association

Total bus ridership grew from 5.5 billion in 1999 to 6.0 billion unlinked passenger trips in 2007, an annual growth rate of 0.9%. Figure 3 shows bus ridership disaggregated into four groups classified by city population. It shows that ridership has grown in both large urban and small urban areas. In large urban areas with a population above 2 million, bus ridership increased from 3.42 billion to 3.74 billion trips per year over the 1999-2007 period, which is a 1.1% annual increase. Ridership in areas with a population between 500,000 and 2 million, on the other hand, did not change much over this period. In urban areas with a population between 100,000 and 500,000, ridership grew from 422 million to 462 million, a 1.1% annual growth rate. The growth rate was the highest for small urban areas with a population below 100,000. For these cities, bus ridership rose by 3.0% per year, from 377 million in 1999 to 479 million in 2007.

PREVIOUS RESEARCH

Taylor and Fink (2003) divided the factors affecting transit ridership into two categories: external and internal. The internal factors are those that transit systems can control, such as fare and service levels, while the external factors are those that are beyond the control of transit systems. As noted by Taylor and Fink, these external factors can include socioeconomic factors, such as employment level, income level, and auto ownership; spatial factors, such as the availability and price of parking and residential and employment densities; and public finance factors. The price of gas is also one of these external factors that can affect ridership.

While there is extensive research on the effects of fares and, to a lesser extent, service levels on transit ridership, fewer studies have analyzed the impacts of automobile operating costs or gas prices. Studies that have attempted to estimate the effect of fuel costs on travel behavior have found that the response to increasing fuel prices is usually small. The demands for car travel and public transit with respect to fuel prices have been found to be quite inelastic.

One of the earliest studies was conducted by Agthe and Billings (1978) of the Tucson, AZ, city bus system using data from 1973 to 1976. They estimated an elasticity of bus ridership with respect to gasoline price of 0.42. This estimate tends to be on the high end of those reported in the literature. Doi and Allen (1986) estimated an elasticity of ridership with respect to real gasoline price of 0.11 for a single urban rail rapid transit line in New Jersey. This study used data from 1978 to 1984.

Other studies have found even lower elasticities, including two Australian studies in the 1990s and one study in Germany. Luk and Hepburn (1993) calculated a short-run Australian travel demand elasticity of 0.07 for a mode shift to transit with respect to fuel price (as cited in Litman 2004), and Hensher (1997) estimated bus demand elasticities in Australia with respect to car operating costs ranging from 0.02 to 0.12. Storchmann (2001) modeled the impact of increases in fuel taxes on public transportation demand in Germany and found that the elasticity of public transit demand with respect to fuel price is 0.07. In 2003, Wallis and Schmidt reviewed the literature, with a focus on research in Australia and New Zealand, and found elasticity values for transit demand with respect to fuel prices ranging from 0.07 to 0.30, with a typical value of 0.15. They also found that, typically, about 30% of people deterred from car use by higher fuel prices switch to public transit.

More recently, Currie and Phung (2007) measured an aggregate elasticity in the United States of 0.12, but they found that it varies by mode. They found that light rail ridership is the most sensitive to gas prices, with elasticities of 0.27 to 0.38, and that bus ridership is quite insensitive, with an elasticity of just 0.04, while that for heavy rail is estimated at 0.17. Currie and Phung (2006) estimated an elasticity of 0.22 in Australia. They argue that the lower U.S. elasticities could partly be explained by lower gas prices in the United States.

Haire and Machemehl (2007) analyzed bus, light rail, heavy rail, and commuter rail ridership for five U.S. cities: Atlanta, Dallas, Los Angeles, San Francisco, and Washington, D.C. In this study, which used ridership data obtained through the APTA, the researchers estimated that the change in bus ridership from a 1% change in fuel prices was 0.22% in Los Angeles, 0.31% in Washington, D.C., 0.54% in Dallas, and 0.24% overall. The overall calculated percentage changes were higher for commuter and heavy rail (0.27% for both) and lowest for light rail (0.7%).

Many of these studies do not distinguish between short- and long-run impacts. Elasticities tend to increase over time as consumers have more options available to them. Research has shown that the long-run elasticity of demand with respect to fares is about 1.5 to 3 times higher than the short-run elasticity (Litman 2004, Hanly and Dargay 1999, Paulley et al. 2006, Goodwin 1992). With respect to changes in fuel prices, it is also reasonable to expect that long-run responses may differ from those immediate reactions.

The Luk and Hepburn (1993) and Storchmann (2001) estimates of 0.07 are considered short-run elasticities. Most of the other estimates are not defined as short- or long-run, but many can likely be considered short-run estimates. Litman (2004) cited a study by TRACE (1999) that estimated that a 10% rise in fuel prices increased transit ridership by 1.6% in the short run and 1.2% over the long run, which indicate short- and long-run elasticities of 0.16 and 0.12, respectively. These estimates decreased in the long run, which the study authors suggested is because fuel price increases caused motorists to buy more fuel efficient vehicles. Litman (2004), however, concluded that the long-run elasticities are likely larger. In reviewing the literature, he provided recommended transit ridership elasticity values with respect to auto operating costs of 0.05 to 0.15 in the short term and 0.2 to 0.4 in the long term. Wallis and Schmidt (2003), on the other hand, did not find conclusive evidence that long-run values differed from those for the short run.

Currie and Phung concluded that there is a wide potential range of elasticity values. Doi and Allen (1986) also remarked that elasticity estimates should differ from city to city and from system to system, reflecting their own idiosyncratic backgrounds. Currie and Phung (2007) demonstrated that elasticities vary between bus and rail and that they can also change over time. Using data from 1995-2005, they estimated the bus elasticity was 0.06 before September 11, 2001, 0.08 between September 11, 2001, and the start of the Iraq war, 0.06 during the Iraq war up until hurricane Katrina, and then 0.04 after Hurricane Katrina. It is not clear, though, why these world events caused the elasticities to change the way they did. The changes are not that large in magnitude, and the authors provided no theoretical explanation for why they would have increased or decreased during this period.

Storchmann (2001) also provided some evidence that elasticities can vary. In this study, he estimated the elasticities based on travel type, dividing travel types into work, school, leisure, shopping, and holiday travel. He found that the elasticity of public transit demand with respect to fuel price is highest for work (0.202) and school (0.121) and lowest for leisure (0.045), shopping (0.031), and holiday (0.016). These results indicate that people who drive for leisure purposes almost never switch to public transportation. They may forgo or consolidate trips in response to rising gas prices, but they will rarely use transit for these trips. Wallis and Schmidt (2003) also found that peak/work elasticities tend to be twice as great as off-peak/non-work elasticities. Storchmann (2001) concluded that there is almost no substitution between the automobile and public transportation for leisure travel. On the other hand, there is much greater substitution between the two modes for work and school travel. Transit ridership by commuters and students is found to be more responsive to gasoline prices. Storchmann found that a decrease of 1% of car use for commuting induces a 4.2% increase in public transportation ridership.

Some research also shows that demand for longer-distance trips on public transportation is affected by gas prices more so than that for shorter-distance trips. Currie and Phung (2008) found that in Melbourne, Australia, the gas price elasticity for bus demand is 0.32 for routes over 25 km and 0.07 for routes under 7 km. Similarly, they found that the gas effects for rail transit are almost three times as large for longer-distance trips. Wallis and Schmidt (2003) also found that as higher gas prices deter people from driving, the longer-distance trips are more likely to be replaced by transit than the short-distance ones.

DEVELOPING A POLYNOMIAL DISTRIBUTED LAG MODEL

Since the price of gas can have a lagged effect on demand for transit, a dynamic model that estimates both short- and long-run elasticities is more appropriate than a static model. Studies that have modeled rail transport demand have used various dynamic models to account for lagged effects (Chen 2007). These types of models could also be applied to an analysis of bus ridership. Since ridership is likely to be affected by not only the current gas price but also past gas prices, using a distributed lag model which estimates ridership as a function of the current gas price and gas prices from previous periods is appropriate, as follows:

(1) $$R_t = \alpha_0 + \beta_0 PG_t + \beta_1 PG_{t-1} + \beta_2 PG_{t-2} + ... + \beta_m PG_{t-m} + u_t$$

where R_t is ridership in time *t*, PG_t is price of gas in time *t*, PG_{t-1} is price of gas in time *t-1*, etc. β_0 represents the immediate impact of gas price on ridership, and the summation of β_0 through β_m equals the long-term impact. The summation of these coefficients can be used to calculate the long-run elasticity in the statistical sense, though that differs from the long-run elasticity in the economic sense since such an elasticity which would require modeling the expectations of consumers.

Estimating a distributed lag model such as that in Equation 1 could be problematic since the lagged gas price variables are likely correlated with each other, creating a multicollinearity problem and making it difficult to isolate the effect of each variable. This problem can be resolved using either the Koyck lag model or the polynomial distributed lag (PDL) model, also known as the Almon lag model. One problem with the Koyck model is that it rigidly assumes geometrically declining weights. The model assumes that β_0 through β_m in Equation 1 are all the same sign and decline geometrically. In the real world, this may not be the case. It is possible that the coefficients for the lagged terms could initially increase before decreasing. For example, the effect of gas price lagged three periods could be greater than that for the current period, since the immediate impact may not be as great as the impact after a few time periods. In this case, the Almon model would be more appropriate. In this model, the lag weights fall on a polynomial.

The Almon model is used to estimate the immediate and longer-term impacts of gas price changes on bus ridership, with additional variables added to account for seasonality, time trends, and changes in services and fares if applicable. The model is applied first using aggregate national data from the APTA and then using data obtained from individual transit systems. Currie and Phung (2007) estimated ridership as a function of gas prices and monthly dummy variables using aggregate APTA data. This study expands upon their research by including additional variables and analyzing specific transit systems. Currie and Phung (2008) noted that their approach simplified the real world influences on transit demand and that, in practice, other variables such as the level of fares, changes in service levels and other factors affect transit usage. Their approach makes the assumption that these other factors are negligible, though for specific transit systems, they could be quite significant.

ANALYSIS OF AGGREGATE BUS RIDERSHIP BY CITY SIZE

As shown in Figure 3, APTA aggregates bus ridership into four classes based on the population size of the metropolitan area. These groups are above 2 million, 500,000 to 2 million, 100,000 to 500,000, and below 100,00. These groups will be referred to as large, medium-large, medium-small, and small cities. Using these data, separate equations were estimated for each of the four population groups. Ridership was estimated as a function of the national gas price and monthly dummy variables, similar to Currie and Phung's model, with the addition of dynamics. Monthly data for January 1999 through December 2006 were used. When APTA releases its quarterly ridership reports, it provides numbers for each month of that quarter plus numbers for the same months of the previous year. The data for the previous year are revised from the original report, and the differences are sometimes significant. Therefore, only the revised numbers were used. The most recent data for

2007 were not included. The gas price data were obtained from the U.S. Department of Energy's Energy Information Administration (EIA), which reports historical gas price data for regions of the United States, some individual states, and the U.S. average. In this case, the U.S. average for all grades of conventional gasoline was used.

The model, which is estimated in double-log form, is derived from the following distributed lag model:

$$\ln R_t = \alpha_0 + \beta_0 \ln PG_t + \beta_1 \ln PG_{t-1} + \beta_2 \ln PG_{t-2} + \ldots \beta_m \ln PG_{t-m} + ?\gamma_i M_i + u_t \tag{2}$$

where M_i is the monthly dummy variable for month *i* (11 dummy variables are included), and the other variables are previously defined. To avoid problems of multicollinearity, the model was estimated using the Almon technique. The degree of the polynomial, *k*, and the number of lags, *m*, were chosen based on minimizing the Akaike Information Criterion (AIC), the Schwartz criteria, and the standard errors of the estimates, as well as theoretical grounds. It is not expected that there would be more than two turning points, and probably not more than one, meaning that setting $k=2$ would be reasonable, and it is expected that the response to gas prices would likely occur within one or two years. Deciding to ride transit instead of driving is not a major long-term decision like buying a new car or house, so while the response might not be immediate, the delay in response would likely be measured in weeks or months, not years. As a result, the lag period of 15 months was chosen for all equations except the medium-large city equation, which has a lag period of 12 months. The polynomial degree is two for the large and medium-large city equations and one for the medium-small and small city equations, where it was determined that a model with no turning points has the best fit.

Bus ridership and gas price were tested for nonstationarity using the Dickey-Fuller unit root test, and all time series were found to be stationary. Since the model may not capture some factors that have changed over time which may affect ridership, a trend variable or yearly dummy variables were added to the equations but then dropped if they were not significant. Yearly dummy variables were significant and included in the medium-large- and medium-small-city equations but were not included in the large- or small-city equations. The equations were also tested for autocorrelation, and autoregressive terms were added to account for this problem.

The estimated coefficient for the current and lagged gas prices are shown in Table 1. Only the statistically significant estimates are shown in this table. There were no significant effects after seven months, so no estimates beyond that point are shown. In all cases, gas price is found to have a positive effect on bus ridership, as expected. For the large and medium-large cities, the response to changes in gas price is fairly quick, with most of the response occurring in the month of or the month after the price change. Some change in ridership also occurs two months after the price change, but after two months, there is no significant response to the change in gas price. The results are different for the small and medium-small cities. For the medium-small cities, there is an immediate ridership increase following a change in the price of gas, but it is a smaller response, and the effect of the price change continues for up to seven months. That is, it takes seven months for the complete effect on bus ridership to occur following a change in gas price. For the small cities, there is no immediate impact on ridership following a change in the price of gas. In fact, there is no significant response until after five months, and then the response is complete after seven months.

Table 1: Impact of Current and Previous Gas Prices on Bus Ridership

	Large	Medium-Large	Medium-Small	Small
	(2,000,000 and over)	(500,000 to 1,999,999)	(100,000 to 499,999)	(Below 100,000)
GP_t	0.059	0.058	0.028	
GP_{t-1}	0.040	0.042	0.026	
GP_{t-2}	0.024	0.028	0.024	
GP_{t-3}			0.022	
GP_{t-4}			0.019	
GP_{t-5}			0.017	0.031
GP_{t-6}			0.015	0.027
GP_{t-7}			0.013	0.022
Cumulative effect	0.123	0.128	0.164	0.081
R^2	0.70	0.87	0.93	0.81

Note: Only the price variables that are statistically significant at the 10% level are shown. The other variables are not shown in the interest of space, but are available upon request.

The cumulative elasticities are 0.12, 0.13, 0.16, and 0.08 for the large, medium-large, medium-small, and small cities, respectively. These elasticities seem to be in line with many of the previous estimates from other studies, and the results also suggest that the impact on bus ridership from changes in gas prices is fairly small in magnitude. The quicker response in larger cities may be explained by the fact that people in large cities are generally more accustomed to public transit. Since per capita transit ridership is greater in larger cities, these people may be quicker to switch to transit during a period of high gas prices than those from smaller cities who may not be as familiar with their available public transportation options. The elasticity is lowest for the smallest cities, indicating that people in small urban or rural areas are less likely to switch to transit. The medium-small cities, though, have the highest response. It is not clear why the response would be greatest in the medium-small cities.

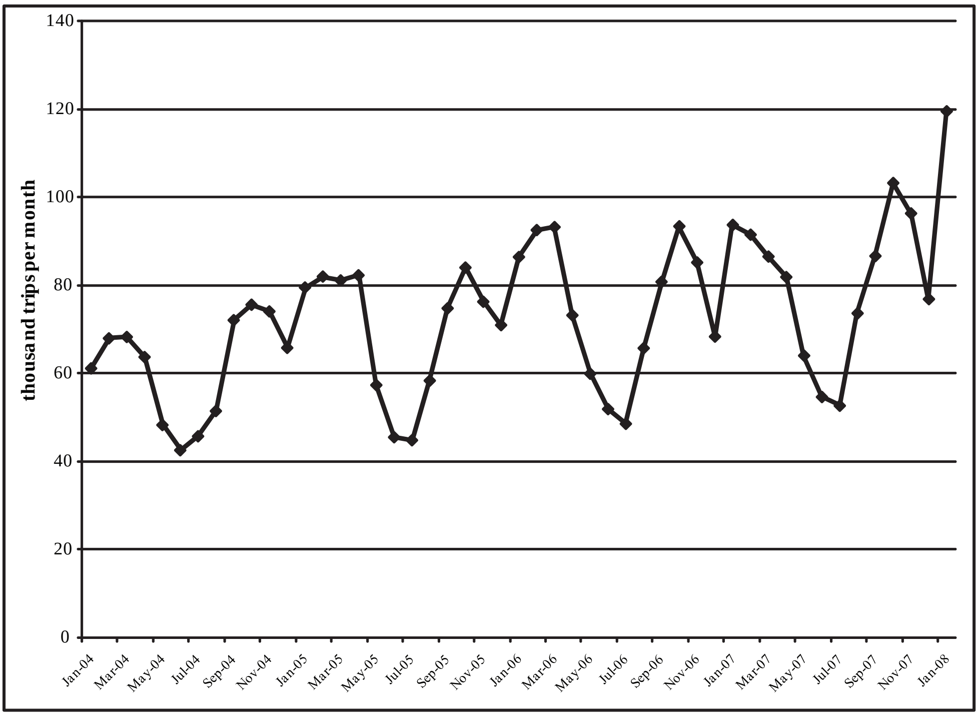
ANALYSIS OF INDIVIDUAL TRANSIT SYSTEMS

While the elasticities from the previous model are similar to those from other studies, it may be more useful to analyze data from specific transit systems. Using aggregate data can hide some of the many other factors which could be affecting ridership for specific agencies, and as Litman (2004) noted, elasticities can vary between cities. By using data for individual transit agencies, it is also possible to model the effects of fares, service levels, and other factors that are affecting ridership. To that end, data were collected from three transit systems, and separate equations were estimated for each. These systems include the Fargo-Moorhead Metro Area Transit (MAT), the Cheyenne Transit Program (CTP), and Clay County Rural Transit (CCRT) of Minnesota. The Fargo and Cheyenne systems operate in small urban areas with populations of approximately 150,000 and 70,000, respectively, and CCRT operates a rural long-distance commuter bus.

Fargo-Moorhead Metro Area Transit

Metro Area Transit (MAT) serves the cities of Fargo, ND, and Moorhead, MN. Fargo and Moorhead form a metro area with a population of about 150,000. For this study, monthly ridership data were obtained for the fixed routes operating in Fargo for January 2004 through January 2008. There has been significant increases in ridership over the last few years on the Fargo fixed routes, rising from 61,157 trips in January 2004 to 119,560 trips in January 2008 (Figure 4). Riding the bus has become more popular among North Dakota State University (NDSU) students in recent years since the U-Pass program makes it free to ride, and the opening of a new NDSU building downtown created a demand for transit between the campus and downtown. During the 2004-2007 period, MAT made a few changes in service which could have affected ridership, including additional night service and route changes. There was no change in fares during this period.

Figure 4: Fargo Fixed Route Ridership



The model used to estimate aggregate ridership was applied to the MAT data with a few revisions such as the addition of service changes. Total ridership was estimated as a function of gas prices, monthly dummy variables, and dummy variables for changes in service. The Minnesota average monthly gas price, obtained from EIA, was used. In this study, the two NDSU-only circulator routes were removed from the analysis because they are not likely affected by gas prices. These routes mainly serve as substitutes for walking or very short-distance driving.

The Dickey-Fuller test shows that the gas price and ridership time series are both non-stationary, but they are trend stationary. Adding a trend variable, therefore, would correct the problem. However, a high correlation between the trend and gas price over this time period could cause a multicollinearity problem. Therefore, the gas price and ridership series were differenced, and the trend variable was removed. The first differences for these variables are stationary. The Almon model was used with a 12-month lag and a second degree polynomial. Autoregressive terms were added to correct for autocorrelation.

The results are shown in Table 2. The immediate effect of gas prices on ridership is not statistically significant. There is a significant effect, though, after one month, and an additional effect is observed after the second month. All the lagged effects greater than two months are insignificant, indicating that the full effect of the change in gas price is observed within three months. The gas price elasticity is 0.113 for the one-month lag and 0.107 for the second-month lag. These results indicate that there is no immediate impact on ridership from a change in gas price, but within three months, there is a cumulative elasticity of 0.22. This elasticity is similar to others reported in the literature and to the 0.16 elasticity estimated for medium-small cities in the previous section, as reported in Table 1.

Table 2: Results for Fargo MAT Routes

	Estimate	t-value
GP_t	0.117	1.56
GP_{t-1}	0.113	1.76*
GP_{t-2}	0.107	1.75*
GP_{t-3}	0.098	1.58
GP_{t-4}	0.087	1.35
GP_{t-5}	0.073	1.10
GP_{t-6}	0.057	0.86
GP_{t-7}	0.039	0.59
GP_{t-8}	0.017	0.28
GP_{t-9}	-0.006	-0.10
GP_{t-10}	-0.032	-0.54
GP_{t-11}	-0.061	-0.94
GP_{t-12}	-0.092	-1.19
Cumulative effect	0.220	
R^2	0.82	

*significant at 10%

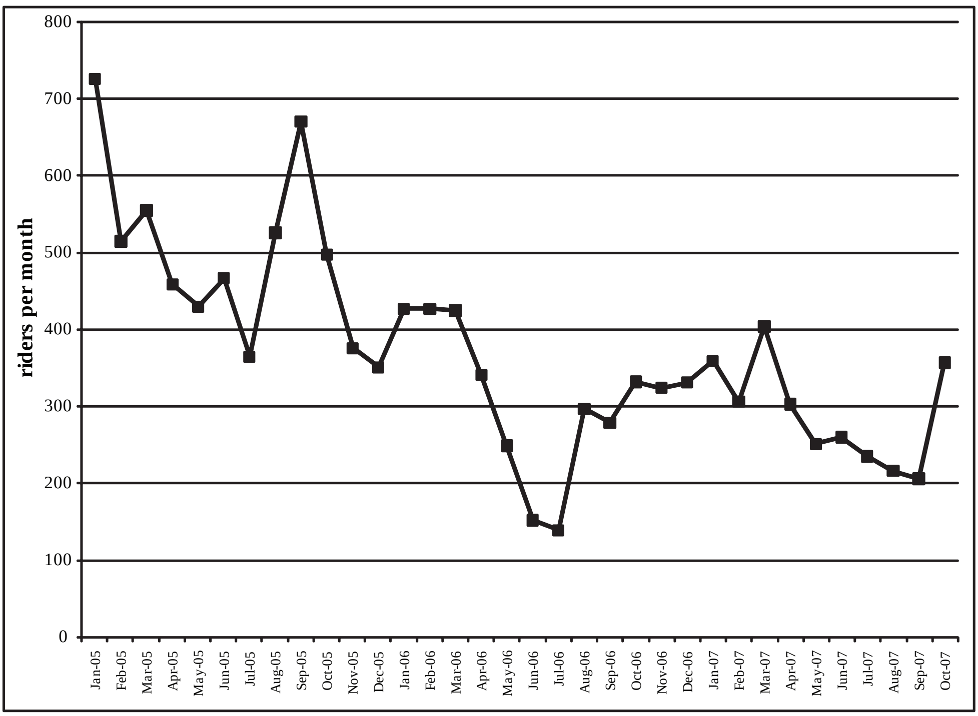
Note: Monthly dummy variables and dummy variables for service changes are not shown in the interest of space, but are available upon request.

Clay County Rural Transit

Clay County Rural Transit (CCRT) operates in Clay County of northwestern Minnesota. This is a mostly rural, partly small urban county along the North Dakota border, with its largest city being Moorhead. CCRT operates demand-response routes and dial-a-ride service along with two daily commuter routes linking Fargo-Moorhead to small towns east of the metro area. One route runs from Barnesville, MN, to Fargo, and other route runs from Detroit Lakes, MN, to Fargo, with stops at towns along the way. The Barnesville to Fargo route is about 25 miles, and the Detroit Lakes to Fargo route is 45 miles. It is reasonable to expect that those commuting long distances may be more sensitive to changes in fuel costs than those who travel short distances and consume less fuel.

Monthly ridership data were obtained from CCRT for January 2005 through October 2007 (Figure 5). CCRT actually had a drop in riders during this period, which could be due to a decrease in service and an increase in fares. The increase in fares occurred in February 2006, and the decrease in service occurred four months earlier in October 2005. An equation was estimated for the Detroit Lakes commuter route. The Barnesville route was not modeled due to inadequate data. Ridership was estimated as a function of gas prices, a dummy variable for the change in fares (equal to 0 prior to the change and 1 afterward), a dummy variable for the change in service (equal to 0 prior to the change and 1 afterward), monthly dummy variables, and a trend variable. The gas price is the average Minnesota price reported by the EIA. To account for month-to-month changes in the number of work days (some months may have more weekend days or holidays, which would affect ridership), the ridership variable was measured as the total number of passengers per month divided by the number of work days in the month. The Almon model was, again, used with a second degree polynomial and a lag period of four months. In these equations, a linear, rather than double-log, model was used, which assumes the elasticities are not constant. All time series were found to be stationary, and autoregressive terms are used to correct for autocorrelation.

Figure 5: Ridership on Clay County Rural Transit Commuter Route



The results show that service is the most important variable affecting ridership for CCRT (Table 3). The effect of the service variable is large in magnitude and highly statistically significant. The magnitude of the effect is a drop in ridership of 9.7 passengers per day following the decrease in service. Considering that the route averaged 24.6 riders per day before the service change, this decline is quite large. The impact of the increase in fares, on the other hand, is found to be statistically insignificant.

Table 3: Results for CCRT Ridership Model

	Estimate	t-value
Intercept	33.481	3.22**
Fare increase	1.353	0.61
Service decrease	-9.711	-3.53**
Trend	-0.132	-1.24
GP_t	0.065	2.17**
GP_{t-1}	0.014	0.94
GP_{t-2}	-0.019	-0.99
GP_{t-3}	-0.035	-2.45**
GP_{t-4}	-0.032	-1.15
R^2	0.93	

* ,** = significance at the 10% and 5% levels, respectively.

Note: Monthly dummy variables are not shown in the interest of space but are available upon request.

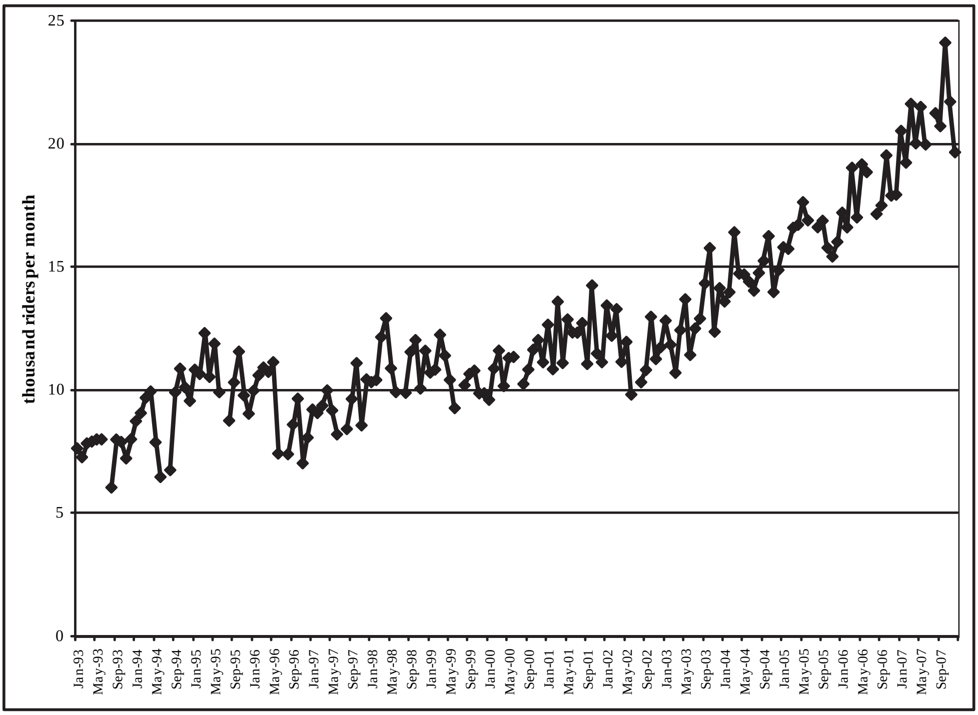
Gas prices have also had some effect on ridership. There is an immediate increase in ridership of 0.065 riders per day following a one cent increase in gas price, which would be one rider per day for every 15 cent increase in gas price. This is a significant increase in percentage terms. In fact, it indicates an elasticity of around one. The results show, though, that the longer-term effect is smaller than the immediate effect, as the increase in ridership is not sustained. After three months, more than half of the riders that switched to the bus revert to their previous habits, as indicated by a decrease in ridership of 0.035 riders per day three months after the price increase. The longer-term effect, therefore, is an increase of 0.031 riders per day following a one cent increase, which would be an increase of one rider per day following a 32 cent increase in the gas prices. This would be an elasticity of roughly 0.5. It is not surprising that the elasticities for this route would be higher than those estimated elsewhere, given that it is for a long-distance commuter route.

Cheyenne Transit Program

The third transit system analyzed is the Cheyenne Transit Program (CTP), which, in terms of size, lies between the smaller CCRT and the larger MAT. CTP serves the city of Cheyenne, WY, which has a metro population of about 70,000. CTP operates six fixed routes that run on one-hour headways six days a week. Data were obtained from CTP that show monthly ridership for 1993 through 2007 (Figure 6). These data include ridership for the fixed routes as well as their paratransit service, a pre-school bus, and a small amount of charter service. CTP also operates a very popular shuttle bus for the Cheyenne Frontier Days shuttle each July, although this is not shown in Figure 6.

As can be seen in Figure 6, ridership has been continually climbing upward. The most significant increase has been from 2002 through 2007, when annual ridership nearly doubled from 147,000 to 260,000. The fixed route service is the largest component, and most of the gain in ridership has been on the fixed routes (Dougherty 2008). Some of the increase in ridership may be driven by changing demographics or socio-economic factors. People moving to Cheyenne from more urbanized areas may be increasing the demand for transit, as these individuals are more accustomed to using public transportation, and they want to continue using it (Dougherty 2008). There may also be an increase in Cheyenne of lower-income, transit-dependent individuals, which would increase ridership (Dougherty 2008). In addition, there have been a number of changes in service over the last several years which likely would have some effect on ridership. These changes included route changes, the implementation of new routes, the elimination of some routes, fewer transfers, and the addition of Saturday service.There have been no increases in fares over this time period. CTP has also implemented programs to assist low-to-moderate-income individuals and persons over 60.

Figure 6: Cheyenne Transit Program Monthly Ridership, 1993-2007



To analyze the CTP ridership, the model was modified to include a trend variable and dummy variables for changes in service. The trend variable may account for increases in ridership over time due to changing population, demographics, socio economic factors, etc. Changes in service may affect this long-term trend, so the service dummy variables are multiplied with the trend to allow the slope of the trend to change as changes in service are made. A total of seven dummy variables were used for changes in service. Monthly dummy variables were again included to account for seasonality. Since the July ridership totals are clearly outliers (excluded from Figure 6), and since they can vary from year to year, separate dummy variables were included for each July. Since such a long time period is used, the price of gas was adjusted for inflation using the Consumer Price Index. The real gas price and ridership are both stationary, and an autoregressive term was added to correct for autocorrelation. A double-log model was used, and the Almon model was, again, estimated. In this case, a second-degree polynomial with a 24-month lag period was estimated since it results in the lowest AIC and Schwartz criteria.

As in the other models, gas prices are found to have a significant positive impact on ridership (Table 4). For CTP, however, the response to changing gas prices is much slower. There is no immediate effect on ridership. The initial response does not occur until six months after the change in gas price, and some response occurs for up to 18 months. The cumulative impact results in a long-term elasticity of 0.47, though it takes 18 months for the full effect to be realized. The trend variable is positive and significant, indicating that ridership has been trending upward, holding gas prices constant, due to various factors which may include changing demographics, population, or socio-economic factors. Changes in service are also found to affect this trend.

Table 4: Results for the Cheyenne Transit Program

	Estimate	t-value
Intercept	9.147	73.78**
Trend	0.0052	2.15**
D1*Trend	-0.0047	-4.18**
D2*Trend	0.0024	3.00**
D3*Trend	-0.0003	-0.85
D4*Trend	0.0008	1.87*
D5*Trend	-0.0002	-0.54
D6*Trend	0.0004	1.24
DTS	0.059	1.67*
GP_t	-0.031	-0.94
GP_{t-1}	-0.019	-0.70
GP_{t-2}	-0.008	-0.38
GP_{t-3}	0.002	0.10
GP_{t-4}	0.010	0.77
GP_{t-5}	0.018	1.62
GP_{t-6}	0.025	2.48**
GP_{t-7}	0.031	3.07**
GP_{t-8}	0.035	3.34**
GP_{t-9}	0.039	3.43**
GP_{t-10}	0.041	3.46**
GP_{t-11}	0.043	3.47**
GP_{t-12}	0.043	3.48**
GP_{t-13}	0.043	3.52**
GP_{t-14}	0.041	3.56**
GP_{t-15}	0.039	3.59**
GP_{t-16}	0.035	3.53**
GP_{t-17}	0.031	3.24**
GP_{t-18}	0.025	2.55**
Cumulative effect	0.47	
R^2	0.96	

Notes: Monthly dummy variables are not shown.
D1=Decreasing routes in June 1996, D2=Decreasing routes in Feb 1998, D3=New routes with fewer transfers in April 2002, D4=Adding Friday night and Saturday routes in June 2004, D5=Cancelling Friday night routes in Sep 2004, D6=Minor route changes, and DTS=Downtown Shuttle.
*,** = significance at the 10% and 5% levels, respectively.

SUMMARY AND CONCLUSIONS

The correlation between increasing gas prices and increasing transit ridership across the United States has led many observers to link the two together, suggesting an increasing number of motorists are opting for public transportation to avoid the high cost of gasoline. However, the few studies that have been conducted suggest that demand for transit with respect to gas price is fairly inelastic. The elasticities reported in the literature vary quite a bit, though. Most estimates lie somewhere between

0.05 and 0.40. This study expands upon the previous research by allowing for dynamics so that both short-run and longer-run elasticities can be estimated, by studying different types of transit agencies, and by analyzing data for specific transit systems.

Since the price of gas can have a lagged effect on demand for transit, a dynamic model that estimates both short-run and long-run elasticities is more appropriate. To this end, a polynomial distributed lag model was developed and applied to aggregate data for transit system in large, medium-large, medium-small, and small urban areas and then to individual transit systems.

The results show that for the large and medium-large cities, the response to changes in gas price is fairly quick, with most of the response occurring in the month of or the month after the price change. For the medium-small cities, there is an immediate ridership increase following a change in the price of gas, but it is a smaller response, and the effect of the price change continues for up to seven months. For the small cities, there is no significant response until after five months, and then the response is complete after seven months. The longer-run elasticities are 0.12, 0.13, 0.16, and 0.08 for the large, medium-large, medium-small, and small cities, respectively. The quicker response in larger cities may be explained by the fact that people in large urban areas are generally more accustomed to public transit, so these individuals may be quicker to switch to transit during a period of high gas prices than those from smaller cities who may not be as familiar with their cities' public transportation options. The elasticity is lowest for the smallest cities, indicating that people in small urban or rural areas are less likely to switch to transit. The medium-small cities, though, have the highest response.

Elasticities can vary between cities, and an aggregate model cannot account for all the various factors that may influence ridership for a specific system, so specific equations were then estimated for three small urban or rural transit systems: Fargo Metro Area Transit (MAT), Clay County Rural Transit (CCRT), and the Cheyenne Transit Program (CTP).

For MAT, the results indicate that there is no immediate impact on ridership from a change in gas price, but there are positive effects one to two months after a price increase. The elasticity is estimated to be 0.22, which is similar to the 0.16 elasticity estimated for medium-small cities. An elasticity of approximately 0.5 is estimated for the CCRT commuter route. The higher response to fuel prices by CCRT riders supports the claim that commuters and long-distance travelers are more likely to switch to transit when gas prices increase. The response to changing gas prices for CTP ridership is slow, but after 18 months, a long-run elasticity of 0.47 is estimated. The slow response is similar to that which was estimated using the aggregate data for small cities, but the long-term effect is much greater for Cheyenne. People who live in areas with lower population densities tend to rely more on the automobile, so they may be less likely to switch to transit given higher gas prices, which would lead to a low elasticity. On the other hand, with fewer people who rely on transit, there are more who have the option of switching between the two modes of travel, which could cause a higher elasticity. The results from the analyses of MAT, CCRT, and CTP ridership show that while gas prices have an impact, other variables, such as changes in service quantity or changes in the community, often play greater roles.

In comparing the results from the different models, the elasticities vary between 0.08 and 0.5, which is fairly consistent with estimates from previous studies. Most of the estimates in the study are in the 0.08 to 0.22 range, with the elasticity estimates for CCRT and Cheyenne being close to 0.5. It should be noted that the long-run elasticities estimated in this paper are long-run elasticities in the statistical sense as opposed to the economic sense. Estimating an economic long-run elasticity would require modeling the expectations of consumers since it represents the response to a price change that is permanent and viewed as such by consumers.

Future research could be conducted to determine if the elasticities change as gas prices increase. At some point, gas prices could reach a level where motorists start becoming more responsive to the higher costs. Additional research could also be done to analyze the effects that gas-price induced ridership gains have on transit costs, since an increase in rush hour demand would create a need for more service. Finally, more research could be conducted to help transit systems manage the continually increasing fuel costs and the associated uncertainty.

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