Effects of Rising Gas Prices on Bus Ridership for Small Urban and Rural Transit Systems

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ABSTRACT

Rising fuel prices have led to significant increases in costs for public transit agencies. A possible benefit from higher gasoline prices, though, is an increase in public transit ridership. This study estimates the effects of gasoline prices on bus ridership by employing a variety of models. Since the price of gasoline can have a delayed effect on the demand for transit, a dynamic polynomial distributed lag model is utilized which measures short-run and longer-run effects. The model is applied to individual transit systems as well as aggregate data for cities grouped by size. A panel data model is also employed, which uses data for eleven transit systems over a period of ten years. These models are applied to small urban and rural transit agencies in the upper Midwest and mountain states. 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. Higher gasoline prices do lead to increased ridership, but the increases in fare revenues are not enough to cover higher fuel expenses for transit systems.

1. INTRODUCTION

Rising fuel prices the last few years have led to significant increases in costs for public transit agencies. As fuel prices continue spiraling upward, the added costs are a significant concern for transportation officials. A possible benefit from higher gas prices, though, is an increase in public transit ridership. As the cost of fueling a car increases, people may seek out ways to reduce fuel consumption, and one such option is public transit. If an increase in gas prices leads to a rise in transit ridership, then fare revenue would increase, and the added fuel costs for the transit operator would at least be partly offset. 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.

If there is any effect on ridership, it would be interesting to see if the impact is a short- or long-run phenomenon. That is, a sudden large price increase may lead to a jump in transit ridership, but will this level of use be sustained? Will riders permanently change their driving habits, or will they eventually accept the higher gas prices and return to their old routines? To adapt to the higher gas prices, they may buy more fuel efficient vehicles or move closer to work. On the other hand, people could start using transit after a spike in gas prices, and their habits could change permanently such that they continue using transit even if gas prices drop.

It is also possible that gas prices may not affect ridership in the same way for all transit agencies. Transit buses that operate longer routes, such as those in rural areas, could be affected differently than those that operate shorter routes. Someone who travels longer distances will likely be more sensitive to changes in gas prices.

The objective of this study is to estimate the effect of gas prices on bus ridership for small urban and rural transit agencies. Secondary objectives are to examine the longer-run implications and to determine if there are different effects for different types of transit operations.

The results of this study are important because they provide some insight about the ability of transit agencies to survive under rising fuel costs. 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, then transit agencies may need to investigate an increase in fares or a decrease in service, or they may need to seek additional public funding.

This paper is organized as follows. In section 2, recent trends in transit ridership and gas prices are documented. Factors affecting transit ridership and the differences between short-run and long-run impacts are discussed in sections 3 and 4. Previous research on the effects of gas prices on transit ridership are reviewed in section 5. To estimate the effect of gas prices on ridership, different econometric models are developed and utilized. Since the impact on ridership from changes in gas prices may not occur immediately, a model which includes dynamics is necessary. To this end, a polynomial distributed lag model, also known as the Almon model, is used. Section 6 provides a description of this model. This model is applied first to aggregate U.S. bus ridership, as presented in section 7, and then to individual transit systems in section 8. Ridership is 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. In section 9, a panel data model is developed and estimated. This model, which provides another approach for estimating the effects of gas prices on ridership, uses data for 11 different small urban transit systems in the upper Midwest and mountain states. The next section compares the increase in fare revenues for these transit systems with the rise in fuel costs. The final section provides a discussion of the results from the various models, and conclusions are presented.

2. 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 Midwest rose from $1.36 in 2002 to $2.82 in 2007 (Figure 2.1). Even in inflation-adjusted terms, the price of gas increased by about 80% from 2002 to 2007. The largest jump in prices occurred in 2005 when the average price increased from about $1.70 per gallon at the beginning of the year to $2.50 in August, which was then followed by a jump to $3.03 after hurricane Katrina. Since this spike in September 2005, the average price per gallon in the Midwest has ranged between $2.05 in November 2005 to a new record high of $3.31 in May 2007. In November of 2007, a time of the year when prices typically are lower, the price of gas climbed, once again, to over $3 per gallon. Prices continued rising in 2008, reaching new highs in the spring.

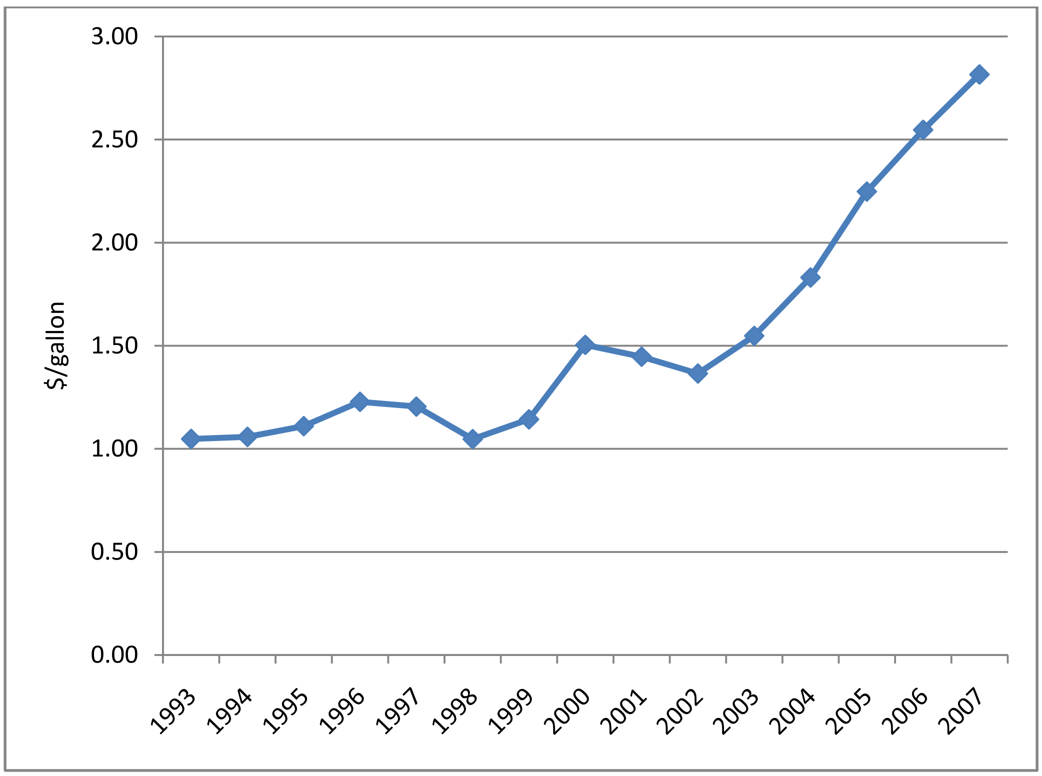


Figure 2.1 Midwest Average Gasoline Price (Source: Energy Information Administration, U.S. Department of Energy)

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. Table 2.1 provides a sampling of the articles in the popular press since 2005 that link the increases in gas prices and transit ridership together.

Table 2.1 Sampling of Media Reports on Gas Prices and Transit Ridership

Date	Article Title	Source
23-Apr-05	High gas prices fuel public transit use	USA Today
20-Aug-05	Bus fares, ridership up in wake of rising gas prices	Waukesha Freeman
11-Sep-05	Gas prices propel rise in carpoolers, metro users	Washington Post
28-Sep-05	Rail, bus ridership rises with gas prices	Associated Press
30-Sep-05	DART ridership increasing along with gas prices	Dallas Business Journal
18-Jan-06	Gas prices spur mass transit use	CBSNews.com
25-Apr-06	Drivers switch to public transit	USA Today
26-Apr-06	Does mass transit benefit from increasing gas prices?	Oakland Tribune
6-May-06	Poll: Americans changing driving habits as gas prices soar	USA Today
30-Dec-06	Bus ridership hits record amid high gas prices	Albuquerque Journal
25-May-07	Bus ridership increases as gas prices rise	Dayton Business Journal
4-Nov-07	High gas prices boost bus use	masslive.com
11-Nov-07	High gas prices increase COTA bus ridership	msnbc.com
26-Nov-07	High gas prices help fill the buses	St. Petersburg Times
26-Dec-07	High gas prices help boost NJ Transit	The Press of Atlantic City
18-Mar-08	Boost in bus riders mirrors gas hike	Fargo Forum
22-Mar-08	As gas prices rise, bus ridership grows	Bangor Daily News
23-Mar-08	Bus ridership up with rising gas prices	Boston.com

Figures 2.2 and 2.3 show the increases in transit ridership in the United States since 1999. 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 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. Some of the growth in light rail ridership can be explained by the construction of new routes. Commuter rail ridership, meanwhile, grew from 392 million to 461 million trips per year over the same period, an annual growth of 2.1%.

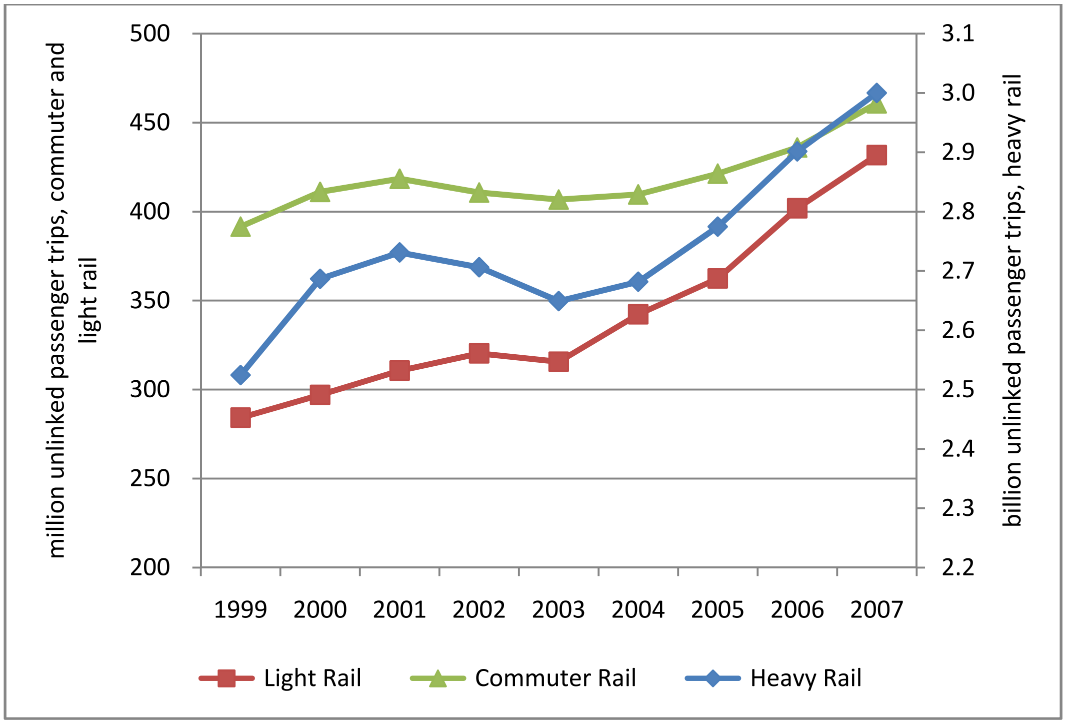
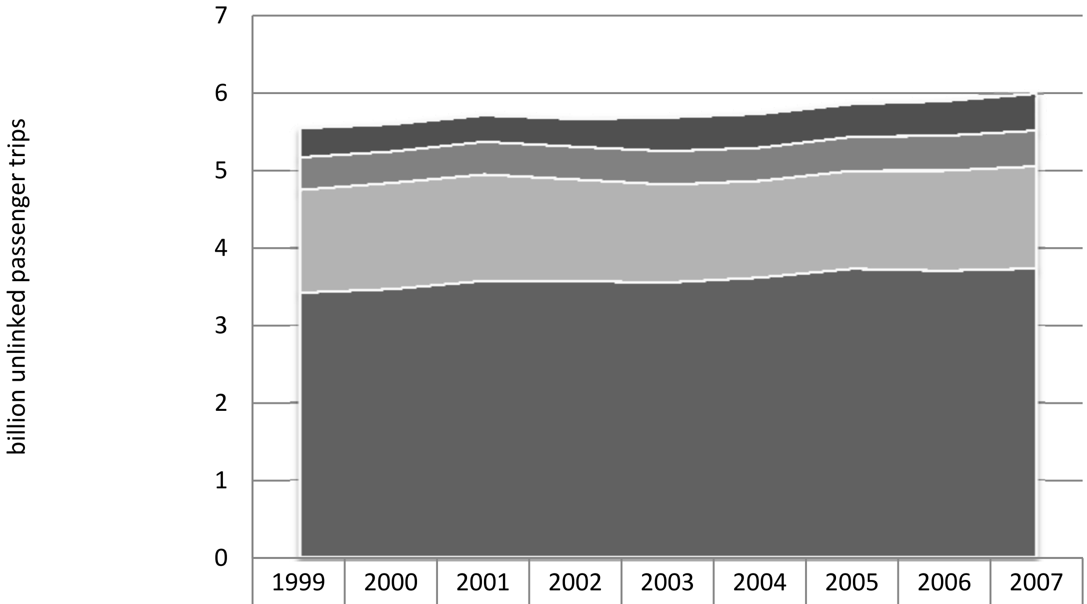


Figure 2.2 U.S. Rail Transit Ridership, 1999-2007 (Source: American Public Transportation Association)

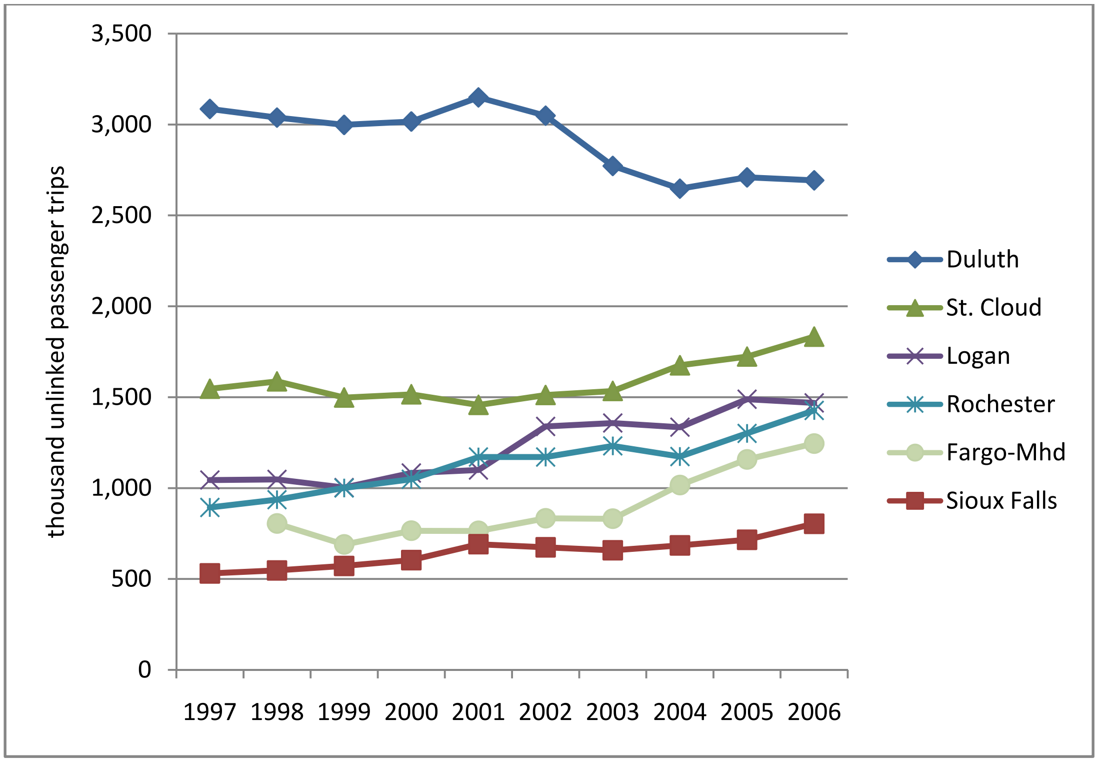
Total bus ridership grew from 5.5 billion in 1999 to 6.0 billion unlinked passenger trips in 2007, an annual growth rate of 0.9%. Figure 2.3 shows bus ridership disaggregated into four groups classified by city population. It shows that ridership has grown in both large urban and small urban areas. In 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 thousand and 2 million, on the other hand, did not change much over this period. In urban areas with a population between 100 thousand and 500 thousand, 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 thousand. For these cities, bus ridership rose by 3.0% per year, from 377 million in 1999 to 479 million in 2007.



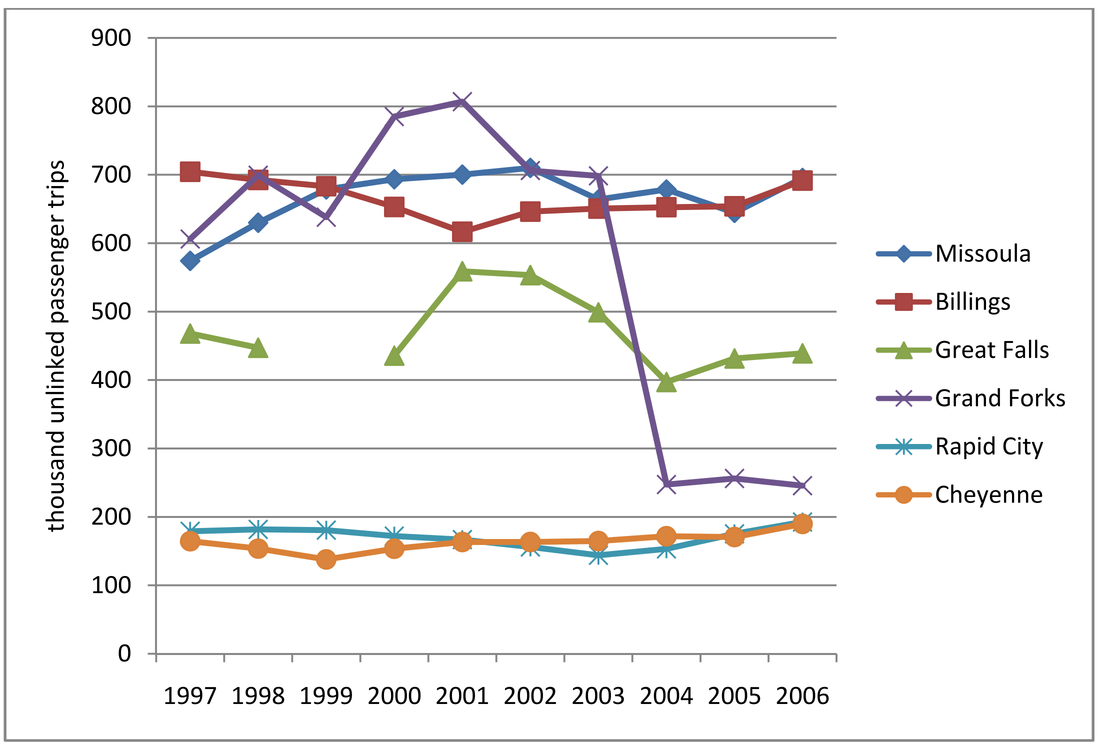
	1999	2000	2001	2002	2003	2004	2005	2006	2007
Below 100,000	0.38	0.35	0.34	0.36	0.44	0.44	0.42	0.45	0.48
100,000-499,999	0.42	0.41	0.42	0.42	0.43	0.43	0.44	0.45	0.46
500,000-1,999,999	1.33	1.37	1.38	1.32	1.27	1.25	1.27	1.30	1.32
2,000,000+	3.42	3.47	3.58	3.57	3.56	3.62	3.73	3.71	3.74

Figure 2.3 U.S. Bus Transit Ridership by City Population Groups, 1999-2007
(Source: American Public Transportation Association)

Since this study focuses on smaller urban areas, ridership data were collected from the National Transit Database for 12 individual transit systems in small urban areas of the upper Midwest and mountain states, listed in Table 2.2. Figure 2.4a shows ridership for 1997-2006 for the six systems with the greatest ridership. Duluth, MN, has the highest ridership of all these systems, by a significant margin, but its numbers have been falling over the last decade, while those for the other five systems in the figure, which include the transit agencies in St. Cloud, MN; Logan, UT; Rochester, MN; Sioux Falls, SD; and the Fargo-Moorhead metro area on the North Dakota-Minnesota border, have all been increasing. The ridership levels for the other six systems are shown in Figure 2.4b. Missoula, MT experienced an increase in ridership until 2003, and Rapid City, SD, and Cheyenne, WY, have seen increases in recent years, while the others have lost ridership or have similar levels as those from a decade ago. Billings, MT, lost ridership between 1997 and 2001 but has since regained it. Most striking in this figure is the substantial drop in ridership for Cities Area Transit in Grand Forks, ND, between 2003 and 2004, which may have been caused by a drop in service. It should be noted that the numbers presented in these two tables are just for fixed bus routes and do not include demand response ridership.



(a)



(b)

Figure 2.4 Bus Ridership for Select Small Urban Transit Systems (Source: National Transit Database)

Table 2.2 Small Urban Transit Systems of the Upper Midwest and Mountain Region

Transit System	**City**
Duluth Transit Authority	Duluth, MN
St. Cloud Metropolitan Transit Commission	St. Cloud, MN
City of Rochester Public Transportation	Rochester, MN
Sioux Falls Transit	Sioux Falls, SD
Fargo-Moorhead Metro Area Transit	Fargo, ND/Moorhead, MN
Billings Metropolitan Transit	Billings, MT
Cities Area Transit	Grand Forks, ND
Missoula Urban Transportation District	Missoula, MT
Great Falls Transit District	Great Falls, MT
Rapid Transit System	Rapid City, SD
City of Cheyenne Transit Program	Cheyenne, WY
Logan Transit District	Logan, UT

Overall, eight of these 12 transit operations have greater ridership than a decade ago. Total ridership for the 12 systems increased by an average of 2.2% per year from 1997 to 2006, and if Duluth, MN, and Grand Forks, ND, are excluded, the annual growth rate is 4.4%. All but three of the systems have experienced growth in ridership since 2003, during the period in which gas prices skyrocketed. There may be other contributing factors though, as suggested by the fact that many of these systems were increasing ridership prior to the large rise in the price of gas. Table 2.3 shows the annual percentage growth rate for 1997-2003 and then 2003-2006 for each transit operation. Five of these systems had higher growth rates prior to the jump in gas prices. Of those that saw ridership growth increase after 2003, the most dramatic changes were for Fargo-Moorhead and Rapid City. For Fargo-Moorhead, though, the introduction of a U-Pass program that allowed college students to ride free and North Dakota State University's opening of an off-campus building, which created a demand for students to travel between campus and downtown, likely had a significant role in increasing ridership.

Table 2.3 Annual Growth Rates in Ridership for Small Urban Transit Agencies for 1997-2003 and 2003-2006

	1997-03	2003-06
Duluth Transit Authority	-1.8%	-1.0%
St. Cloud Metropolitan Transit Commission	-0.1%	6.1%
The Logan Transit District	4.5%	2.6%
City of Rochester Public Transportation	5.5%	5.0%
Fargo-Moorhead Metro Area Transit	0.7%	14.4%
Sioux Falls Transit	3.7%	6.9%
Missoula Urban Transportation District	2.4%	1.5%
Billings Metropolitan Transit	-1.3%	2.1%
Great Falls Transit District	1.1%	-4.2%
Cities Area Transit	2.4%	-29.4%
Rapid Transit System	-3.6%	10.2%
City of Cheyenne Transit Program	0.0%	4.8%

When evaluating the impact of gas prices on bus ridership, a simple correlation between the two, as reported in the numerous press articles, is not enough. Other factors that may be affecting ridership, such as changes in fares or services, socio-economic factors, and the type of changes mentioned for Fargo-Moorhead, need to be considered. The next section will provide an overview of factors that affect transit ridership.

3. FACTORS AFFECTING RIDERSHIP

Taylor and Fink (2003) divided the factors affecting transit ridership into two categories: external and internal. The external factors are those beyond the control of transit systems, while the internal ones are those they can control. The price of gas is one of these external factors that can affect ridership. Other external factors, as noted by Taylor and Fink, 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.

An increase in the employment level can have a positive impact on transit ridership because it creates an increased demand for commuter travel. A number of studies have included the employment level as a variable in their ridership analyses, and they have found that it is a significant factor (Taylor and Fink 2003). Studies have also found that income level has a negative effect on ridership, suggesting that transit is an inferior good (Taylor and Fink 2003). Spatial factors are also important. Low availability and high cost of parking have been found to positively impact ridership (Litman 2004, Taylor and Fink 2003). Increases in residential and employment densities have also been found to have a positive impact on ridership, as compact developments are more conducive to efficient transit operations (Paulley et al. 2006, Taylor and Fink 2003).

Factors affecting ridership that transit systems can control include fare levels, service quantity, and service quality. There is extensive literature on the effects of fare changes on ridership. Litman (2004), Hanly and Dargay (1999), and Goodwin (1992) provided a review of these studies. An increase in fares, naturally, has a negative impact on ridership, but the response is generally found to be somewhat inelastic. Elasticity estimates have ranged between -0.2 to -1.0.[1] Long-run elasticities have been found to be greater than those for the short-run, which will be discussed in greater detail in a later section. Litman (2004) noted that no single transit elasticity value can be applied in all situations, and that various factors affect price sensitivities, including user type, trip type, geography, type of price change, direction of price change, time period, and transit type. Specifically, Litman concluded that transit-dependent riders are less price sensitive than discretionary riders (those who have the option of using a car); commute trips are less price sensitive than non-commute trips; large cities tend to have lower price elasticities than suburbs and smaller cities; elasticities increase somewhat as fare levels increase; fare increases affect ridership more so than fare decreases; long-run elasticities are greater; and bus and rail have different elasticities since they serve different markets. Hanly and Dargay (1999) also found that commuting trips and peak travel are less sensitive to fare changes, and higher income groups are more sensitive to changes in bus fares, likely due to lower-income groups having fewer options.

One interesting observation is that riders in large cities tend to respond less to changes in fares than do those in the suburbs or small cities. Litman (2004) suggested this is due to large cities having more transit-dependent riders, greater traffic congestion, higher parking costs, and improved transit service. Paulley et al. (2006) also concluded that people in areas with low population densities tend to rely more on cars and less on public transport, so they are more likely to have the option of switching to car travel if fares increase.

While these observations are most often made with regard to the response of ridership to fare changes, which is the own-price elasticity, similar observations may be extended to cross-price elasticities. For

[1] The response in ridership to a change in price or some other factor can be measured using the elasticity. The elasticity is the percentage change in ridership due to a 1% change in price (or some other factor). A fare elasticity of -0.5, for example, means that a 1% increase in fare leads to a 0.5% decrease in ridership.

example, the effect of gas price on transit ridership may also be influenced by the user type, trip type, geography, etc., which will be discussed further in a later section.

The other major factor that transit systems can control, beside fares, is the service level. Service includes both service quantity, which can be measured by coverage and frequency, and service quality. An increase in coverage (that is, a new route covering a new area) is expected to increase ridership for a transit system because it improves access for potential riders, and an increase in frequency should attract riders since it decreases wait time and increases convenience. Booz, Allen, Hamilton (2003) concluded that service frequency, access to a bus stop, the likelihood of a transfer, and in-vehicle time all influence ridership. Among the service quality factors that can affect transit use, Taylor and Fink (2003) include bus information, on-street service, station safety, customer safety, safety en-route, cleanliness, route structuring, coordinated arrival and departure at focal points, strong marketing programs, and ITS-delivered transit information.

4. SHORT-RUN VERSUS LONG-RUN EFFECTS

Elasticities tend to increase over time as consumers have more options available to them. An increase in bus fares, for example, may not immediately lead to a significant decrease in ridership because many riders may not have other available options, but over time, some of those riders may buy a car, move within walking distance of work, find people to carpool with, etc. in response to the higher fares. Therefore, the long-run response may be more elastic than the short-run response. Many studies have found that this, in fact, is the case. 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). Paulley et al. (2006) found that the bus fare elasticity averages around -0.4 in the short run, -0.56 in the medium run, and -1.0 in the long run. Fearnley and Bekken (2005) found that these elasticities are generally -0.2 to -0.5 in the short-run and -0.4 to -1.3 in the long-run. Short- and long-run estimates have also been made for the elasticity of public transit demand with respect to the supply of service provided. These elasticity estimates range from 0.2 to 0.7 in the short-run and from 0.4 to 1.1 in the long-run.

It is important for transit operators to take into consideration the long-run response when making changes to fares or services. If only the short-run elasticity is estimated, then it appears that riders are not very responsive to changes in fare or service, and since ridership would drop by only a small amount, an increase in fares would increase total revenue. In the long-run, however, revenues may not increase by as much as more riders respond to the higher fares. Some studies have estimated long-run elasticities of -1.0, which would indicate fare revenues would not increase at all in the long-run due to the subsequent drop in ridership.

With respect to changes in fuel prices, it is also reasonable to expect that long-run responses may differ from those immediate reactions. An individual's travel behavior may not immediately respond to a change in fuel price for various reasons. Following a large price increase, consumers, for example, may expect that price will return to previous levels, so they do not change their behavior, or perhaps they are not aware of alternatives such as public transit. Once people are accustomed to driving their automobile wherever they want to go, it may not be easy to get them to change their habits, so a response to rising gas prices may be slow. Over time, though, some may decide that car travel is becoming too expensive, so they seek alternatives such as mass transit. Individuals could also respond by purchasing more fuel efficient vehicles or moving closer to their place of work. These are major, long-term decisions that are not immediately made after every spike in gas prices. Therefore, one expects the long-run elasticity of fuel demand with respect to fuel price to be higher than the short-run elasticity. The long-run elasticity of transit demand with respect to fuel price could also be higher than the short-run elasticity, but it is not as obvious. The decision to ride transit is not a long-run decision like purchasing a home or car. If gas prices decline, riders may quickly return to their old habits of driving their cars. There is little research on long-run vs. short-run elasticities of transit demand with respect to fuel prices.

5. PREVIOUS RESEARCH ON THE EFFECT OF GAS PRICES ON RIDERSHIP

While there is extensive research on the effects of fares 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 found to be quite inelastic. Table 5.1 shows the elasticity estimates for different studies that have analyzed the impacts of fuel costs or automobile operating costs of transit ridership.

Table 5.1 Previous Estimates of Public Transit Demand Elasticities with Respect to Gas Prices

Study	Short-run	Long-run	Not defined	Notes
Agthe and Billings 1978			0.42	Tucson city bus system, 1973-1976
Currie and Phung 2007			0.04	0.12 for all transit
Doi and Allen 1986			0.11	New Jersey rail line, probably short-run
Haire and Machemehl 2007			0.24	For all transit, not just bus
Hensher 1997			0.02 - 0.12	With respect to car operating costs; based on a survey of residents of Newcastle, Australia; as cited in Litman 2007
Litman 2007	0.05 - 0.15	0.2 - 0.4		With respect to car operating costs
Luk Hepburn 1993	0.07			Australia, as cited in Litman 2007
Storchmann 2001	0.07			Germany
TRACE 1999	0.16	0.12		As cited in Litman 2007

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, indicating that a 1 percent increase in the price of gas led to a 0.42 percent increase in ridership. This estimate tends to be on the high end of those reported in the literature (Table 5.1). 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 1978-1984. 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) and Haire and Machemehl (2007) provided estimates of the effects of gas prices on transit ridership. 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, DC. In this study, which used ridership data obtained through the American Public Transportation Association (APTA), the researchers plotted the percentage changes in ridership from the previous month against the percentage change in fuel cost for the previous month. They estimated that the change in bus ridership from a 1% change in fuel prices was 0.22% in Los Angeles, 0.31% in Washington, DC, 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%). While Currie and Phung found that light rail ridership is the most responsive to gas prices and bus ridership the least responsive, Haire and Machemehl found the opposite.

Many of these studies do not distinguish between short- and long-run impacts. 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) which 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. This represents short- and long-run elasticities of 0.16 and 0.12, respectively. Unlike the bus fare elasticities, 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 demonstrated that elasticities vary between bus and rail, and 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 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% in 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.

6. 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 that estimates ridership on the current gas price and gas prices from previous periods seems to be reasonable, as follows:

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

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.

Estimating a distributed lag model such as this 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 American Public Transportation Association (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.

7. ANALYSIS OF AGGREGATE BUS RIDERSHIP

As shown in Figure 2.3, APTA aggregates bus ridership into four classes based on the population size of the metropolitan area. These groups are above 2 million, 500 thousand to 2 million, 100 thousand to 500 thousand, and below 100 thousand. These groups will be referred to as large, medium-large, medium-small, and small cities. Using these data, separate equations are estimated for each of the four population groups. Ridership is 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 are 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 is used.

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

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

where M_i is 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 is 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 response to gas prices could 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 2 for the large and medium-large city equations and 1 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 that 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 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 7.1.[2] 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

[2] The results for the monthly and yearly dummy variables are not shown here in the interest of space, but they are available from the author at request. The monthly dummy variables are significant, indicating seasonality in bus ridership, and some yearly dummy variables are significant, indicating changes over time.

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 7.1 Results from Aggregate Model

	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.

8. 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 that 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 about 150,000 and 70,000, respectively, and CCRT operates a rural long-distance commuter bus.

8.1 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. MAT currently operates 22 fixed routes as well as paratransit service. This analysis will focus on the fixed route ridership. Eight of these routes operate in Moorhead, with the remainder in Fargo. For this study, monthly ridership data were obtained for the fixed routes operating in Fargo for January 2004 through January 2008. Figure 8.1 shows 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. The figure also clearly shows substantial seasonality in ridership. This seasonality can also be seen in Figure 8.2. Ridership drops in the summer months, increases in the fall until peaking in October, decreases in December and then increases again at the beginning of the year. Figure 8.2 also shows a continued year-to-year increase in ridership regardless of the month. In almost every month, ridership increases from one year to the next.

The seasonality can be explained, to a large extent, by the use of MAT buses by college students. MAT runs two circulator buses on and near the North Dakota State University (NDSU) campus. These two buses, routes 31 and 32, are very popular during the school year, but do not operate in the summer. Ridership on the routes also declines in December when students have winter break. The effect of college students on MAT ridership is quite significant. Even though route 32 only operates during school days and not at all in the summer, it has the highest ridership of all the Fargo routes. In fact, since 2004, it has consistently accounted for about 16% of total MAT fixed-route ridership in Fargo. The use of MAT buses by college students can also be illustrated by the significant increase in ridership in route 13, which connects NDSU to downtown Fargo and the main transit hub. There are two buses that run on route 13 – 13a and 13b – on a 15-minute interval. Route 13b actually provides a more direct route between campus and downtown by skipping the most northern part of the route. If 13a and 13b are combined, ridership on this route actually surpassed that for route 32 in 2007. Total ridership on route 13 increased 85% from 2004 to 2007. Riding the bus has become more popular among college students in recent years since the U-Pass program makes it free to ride, and the opening of a new building downtown for architecture students has created a demand for transit between the campus and downtown. As would be expected, ridership on route 13 also exhibits a substantial amount of seasonality. Route 13b, in fact, does not operate in the summer. While ridership on route 13 has been increasing among both students and non-students, most of the increase has been from students. This can be illustrated by the fact that, from 2004 to 2007, ridership roughly doubled during the school year but grew by just 23% in June and July (which is still significant). It may also be true that non-students could ride the bus less during the summer. Ridership totals on other routes indicate that this may, in fact, be the case, but the seasonality on these other routes is much less pronounced.

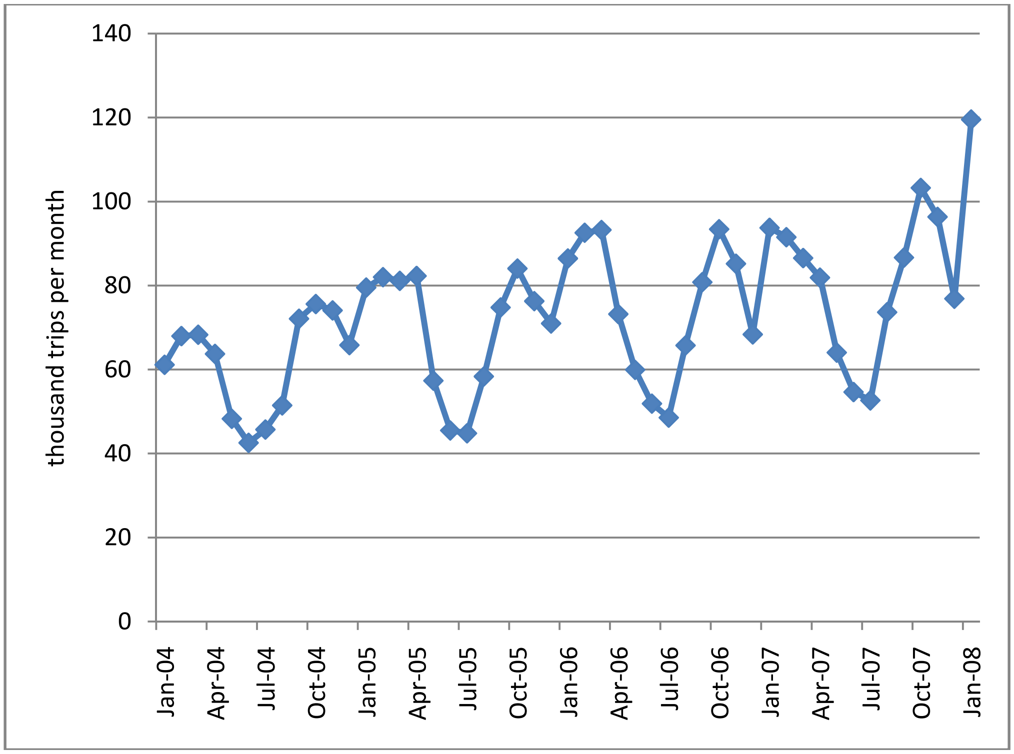


Figure 8.1 Fargo Monthly Fixed Route Ridership

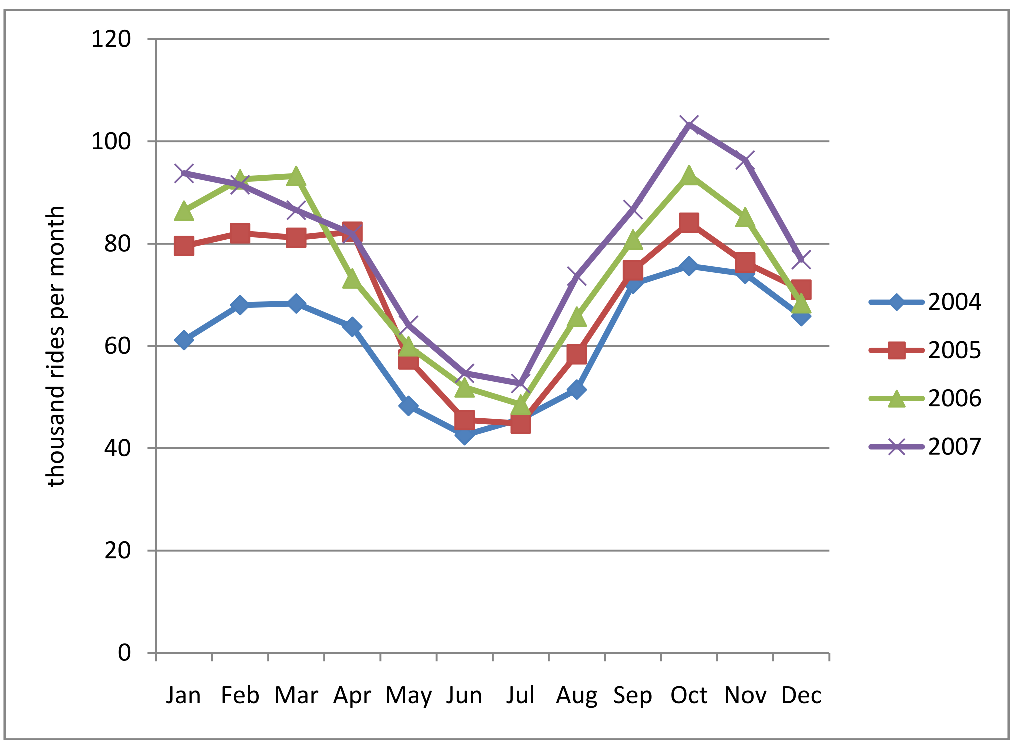


Figure 8.2 Seasonality in Fargo Ridership, and Year-to-Year Changes

The effect of college student ridership is depicted in Figure 8.3. The top part of the graph is ridership on routes 31 and 32. The middle section shows ridership for route 13, and the remainder is ridership for the rest of the routes. Much of the seasonality, along with the dramatic increase, is removed once those routes are excluded, but there is still a continued upward trend in ridership.

During the 2004-2007 period, MAT made a few changes in service which could have affected ridership. Route 13b was added in August 2004, the same time that the downtown NDSU building opened; night service was added for route 16 in January 2005; and in August 2007, route 19 was eliminated, route 21 was added, and changes were made to routes 15 and 22. There was no change in fares during this period.

The model used to estimate aggregate ridership is applied to the MAT data with a few revisions such as the addition of service changes. Total ridership is 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, is used. In this study, routes 31 and 32 are removed from the analysis because these are NDSU-only circulator routes which 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 is used with a 12-month lag and a second degree polynomial. Autoregressive terms are added to correct for autocorrelation.

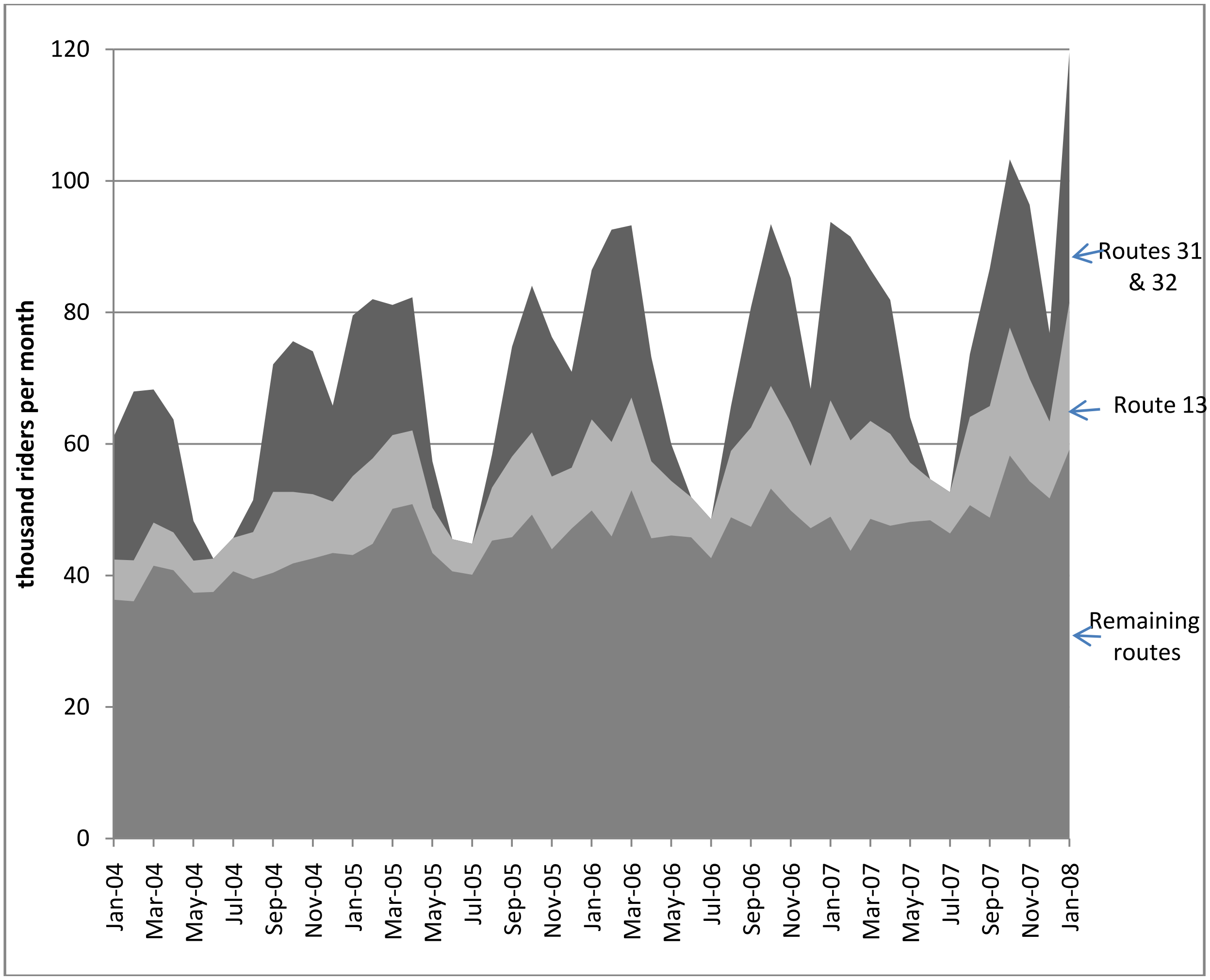


Figure 8.3 A Disaggregated View of Fargo Ridership

8.1.1 Results

The results are shown in Table 8.1. 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, which means that a 10% increase in gas price would result in a 2.2% increase in ridership. 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 7.1.

Table 8.1 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}	-0.091	-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.

8.2 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 daily commuter routes linking Fargo-Moorhead to small towns east of the metro area in Minnesota. The system offers two commuter routes, and each route runs one bus to Fargo in the morning and one return bus in the evening. One route runs from Barnesville to Fargo, with a stop in Sabin, and the other bus runs from Detroit Lakes, with stops in Audubon, Lake Park, Hawley, and Glyndon, before arriving in Fargo. The Barnesville to Fargo route is about 25 miles, and the Detroit Lakes to Fargo route is 45 miles.

A number of workers commute long distances from these small towns to Fargo-Moorhead. Changes in the price of gas have significant impacts on the cost of commuting for these individuals. A round-trip commute for those in the area that CCRT serves is about 50-90 miles. A $1 increase in the price of gas can increase the cost of commuting for someone in Detroit Lakes by more than $80 per month. It is reasonable to expect, therefore, that those commuting long distances may be more sensitive to changes in fuel costs than those who travel short distances and consume less fuel. As noted earlier, previous research has indicated that long-distance trips on public transportation are affected more by gas prices (Currie and Phung 2008, Wallis and Schmidt 2003) and that gas price elasticities are highest for commuters (Storchmann 2001, Wallis and Schmidt 2003). Ridership on the CCRT commuter routes could increase with the increasing gas prices as more commuters may opt for alternatives to reduce their transportation costs.

Monthly ridership data were obtained from CCRT for January 2005 through October 2007. Data prior to 2005 were not available. Figure 8.4 shows the ridership numbers over this period. 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. Both of these actions were partly in response to higher fuel costs being borne by the agency. Prior to the change in service, three shuttle buses would drop each rider off directly at his or her place of work in the morning and then pick up him or her there again in the evening. Beginning in October 2005, CCRT discontinued the shuttle buses and, instead, dropped riders off at the Ground Transportation Center in downtown Fargo where they could then transfer to a MAT bus. A similar procedure was adopted for the end of the day, where riders would take a MAT bus back to the central station before boarding the CCRT bus. It is expected that this decrease in service may have had a negative impact on ridership because reaching their place of work became more inconvenient for some of the commuters, especially those who were not well served by the MAT routes. The changes also amounted to an additional fare increase because, while commuters received a free transfer in the morning, they had to pay the fare to ride the MAT bus back to the central station in the evening.

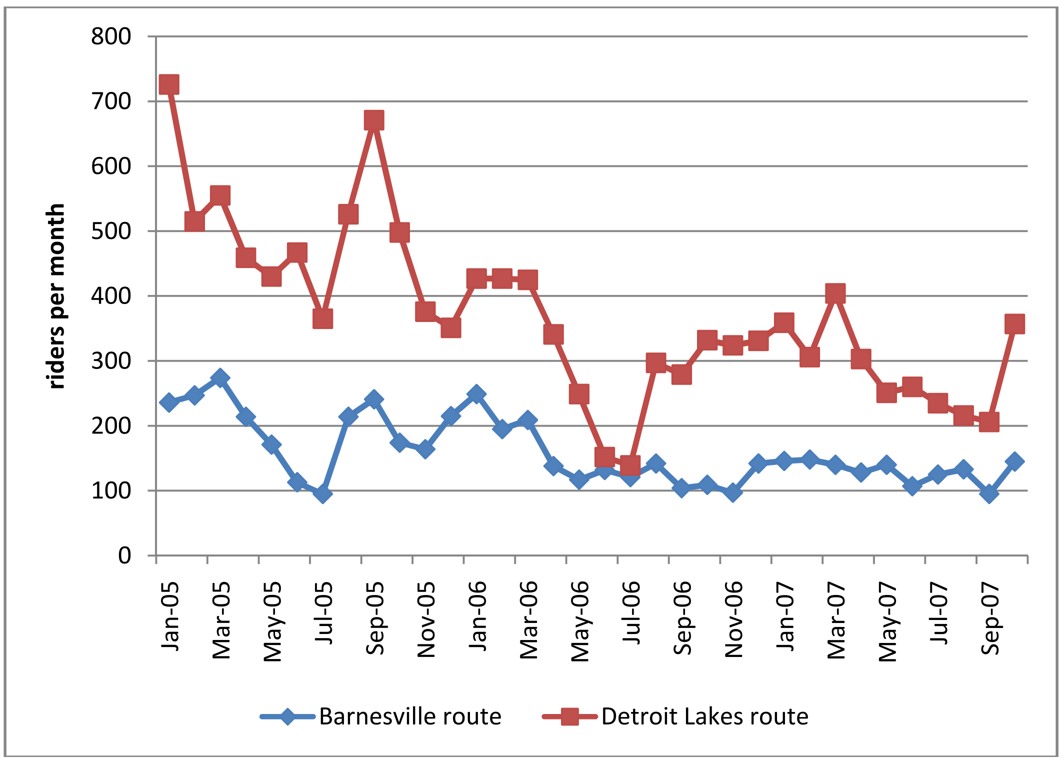


Figure 8.4 Ridership on Clay County Rural Transit Commuter Routes

Separate equations are estimated for the two commuter routes. Ridership is 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. Monthly data from January 2005 through October 2007 are used. 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 is measured as the total number of passengers per month divided by the number of work days in the month. The Almon model is, again, used. A second degree polynomial is used with a lag period of four months. In these equations, a linear, rather than double-log, model is used, which assumes the elasticities are not constant. All time series are found to be stationary, and autoregressive terms are used to correct for autocorrelation.

8.2.1 Results

The results show that service is the most important variable affecting ridership for CCRT (Table 8.2). For both routes, the effect of the service variable is large in magnitude and highly statistically significant. These results show that the decrease in service that started in October 2005 had a significant negative effect on ridership for both routes. The magnitude of the effect is a drop in ridership of 9.7 passengers per day on the Detroit Lakes route and 3.3 passengers per day on the Barnesville route. Considering that the CCRT routes averaged 24.6 and 9.4 riders per day on the two routes, respectively, before the service change, this decline is quite large. The increase in fares is found to have a less important impact on ridership. The fare increase is associated with a decline in ridership of 1.6 passengers per day for the Barnesville route, and the effect for the Detroit Lakes route is statistically insignificant.

Table 8.2 Results for CCRT Ridership Model

	Detroit Lakes Route		Barnesville Route	
	Estimate	t-value	Estimate	t-value
Intercept	33.481	3.22**	-3.637	-1.03
Fare increase	1.353	0.61	-1.581	-2.05*
Service decrease	-9.711	-3.53**	-3.261	-3.27**
Trend	-0.132	-1.24	-0.142	-3.70**
GP_t	0.065	2.17**	0.042	5.00**
GP_{t-1}	0.014	0.94	0.025	4.76**
GP_{t-2}	-0.019	-0.99	0.012	1.97*
GP_{t-3}	-0.035	-2.45**	0.004	0.89
GP_{t-4}	-0.032	-1.15	0.001	0.13
R^2	0.93		0.93	

*denotes significance at the 10% level

**denotes significance at the 5% level

Note: Monthly dummy variables not shown in the interest of space.

Gas prices have also had some effect on ridership. By glancing at the change in ridership since 2005, one might conclude that since the number of passengers has fallen, the increase in gas prices has not had a positive impact. These results show, though, that changes in service and fares are largely responsible for the decline. It may be possible that the rise in gas prices has prevented ridership from falling even further. Results indicate that, to some extent, this is the case. For the Detroit Lakes route there is an immediate increase in ridership of 0.065 riders per day following a 1 cent increase in gas price, which would be one rider per day for every 15 cent increase in gas price. This may seem like a small effect, but given that the route has averaged roughly 17 riders per day during the period, it is a significant increase in percentage terms. In fact, it indicates an elasticity of around 1, which is quite high. 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 who 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 1 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, depending on the current gas price and ridership rate, which is still fairly high.

For the Barnesville route, there is an immediate increase of 0.042 riders per day following a 1 cent gas price increase and additional increases over the next two months. The entire effect is observed within three months of the price change, and unlike the Detroit Lakes route, the longer-term effect is larger than the immediate effect. The cumulative effect after three months is an increase in ridership of 0.074 per day following a 1 cent gas price increase, which would be one rider per every 13.4 cent increase in the gas price. Given that the Barnesville route has averaged just 7.5 riders per day during this period, this is a substantial increase in ridership in percentage terms. The elasticity would be roughly equal to 4.

It is not surprising that the elasticities for these routes would be higher than those estimated elsewhere, given that they are for long-distance commuter routes. The estimates for the Detroit Lakes route may be reasonable, but the extremely high elasticity for the Barnesville route is unexpected and seemingly unreasonable. The result could be the product of a small dataset and low ridership on the route. A change in ridership of just one or two riders per day is actually a significant change in percentage terms, which could lead to the estimation of elasticities that seem to be unrealistically large and probably not sustainable. A dataset longer than 34 months could also provide better results.

It should also be noted that the effects for gas prices are not robust. One of the weaknesses of the Almon model is that choosing the number of lags and the degree of the polynomial is somewhat arbitrary, and when the model is changed by altering the number of lags for the polynomial, adding or removing variables, or changing the functional form from linear to double log, the effect of gas prices in the CCRT model tends to change. Therefore, there is less confidence in the results of the model. The effects of the service and fare variables, though, are quite robust.

8.3 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, Wyoming, which has a metro population of about 70,000. CTP operates six fixed routes that run on one-hour headways six days a week. CTP also operates a paratransit service, service for a preschool program, and a shuttle for Cheyenne Frontier Days every July. Data were obtained from CTP that show monthly ridership for 1993 through 2007, a much longer time frame than what was available from the other transit agencies. The data include ridership for all services, though, and not just the fixed routes. The Cheyenne Frontier Days shuttle is a very popular bus, and as a result, ridership numbers in July are significantly higher than they are the rest of the year.

Figure 8.5 shows monthly CTP ridership for 1993 through 2007, excluding July. As can be seen in this figure, ridership has been continually climbing upward. The most significant increase has been from 2002 through 2007, when annual ridership nearly doubled from 148,313 to 260,148. The ridership totals in Figure 8.5 include numbers for both fixed routes and paratransit, as well as the preschool bus and a small amount of charter service. The fixed route service is the largest component, though, and most of the gain in ridership has been on the fixed routes (Dougherty 2008).

Rising gas prices may partly explain the rise in ridership, but there may also be other contributing factors. Some of the increase may be driven by changing demographics or socio-economic factors. People moving to Cheyenne from more urbanized areas may be increasing 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). CTP has also implemented programs to assist low- to moderate-income individuals and persons over 60.

There have also been a number of changes in service over the last several years, which likely would have some effect on ridership: new routes were implemented in September 1994; the number of routes was decreased in June 1996 and again in February 1998; new routes with less transfers were implemented in April 2002; a downtown shuttle was in service from 2003 through July 2006; Friday routes were extended to 11 p.m. and Saturday routes were added in June 2004; the late night Friday routes were discontinued in September 2004; and minor changes were made to the routes in January 2006, including the addition of new stops. There have been no increases in fares over this time period.

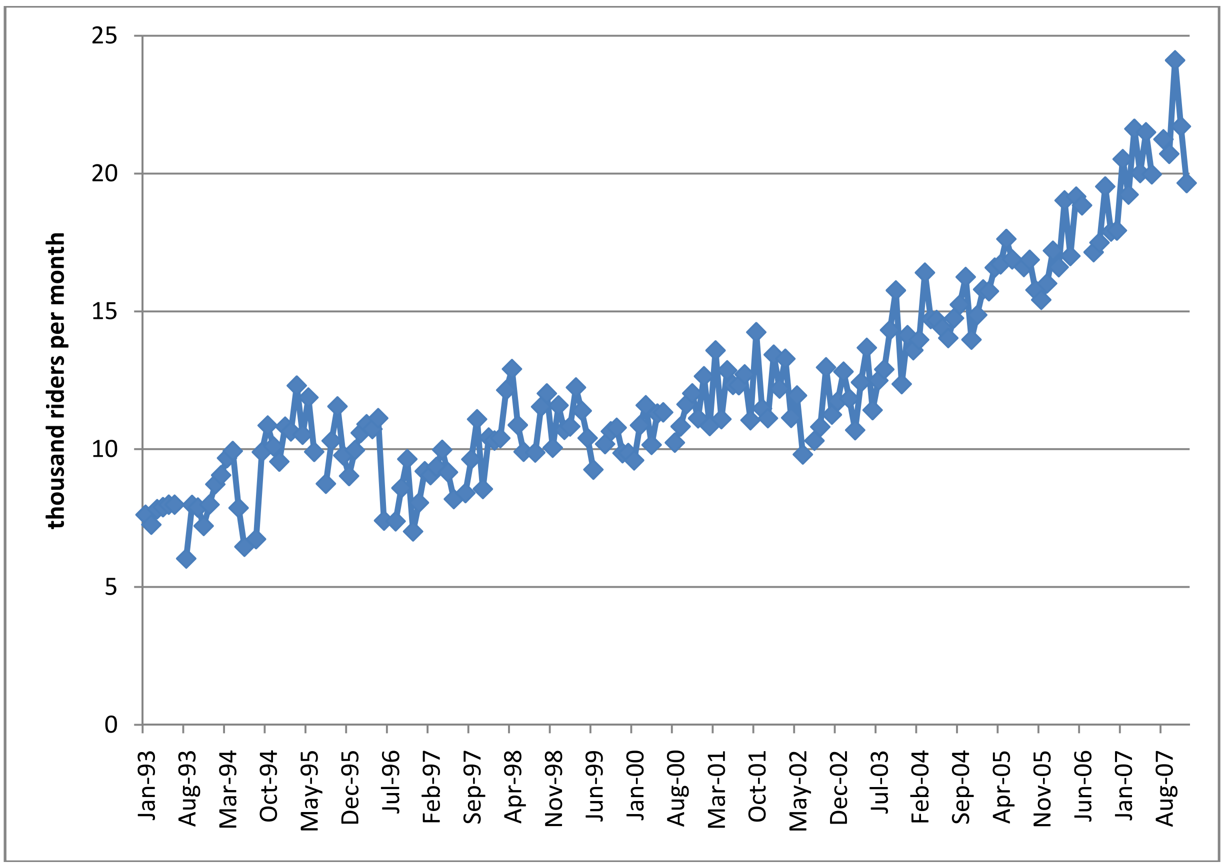


Figure 8.5 Cheyenne Transit Program Monthly Ridership, 1999-2007

To analyze the CTP ridership, the model is 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 are used for changes in service. Monthly dummy variables are again included to account for seasonality. Since the July ridership totals are clearly outliers, and since they can vary from year to year, separate dummy variables are included for each July. Since such a long time period is used, the price of gas is adjusted for inflation using the Consumer Price Index. The real gas price and ridership are both stationary, and an autoregressive term is added to correct for autocorrelation. A double-log model is used, and the Almon model is, again, estimated. In this case, a second-degree polynomial with a 24-month lag period is estimated since it results in the lowest AIC and Schwartz criteria.

8.3.1 Results

As in the other models, gas prices are found to have a significant positive impact on ridership (Table 8.3). 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, indicating that a 10% increase in gas price results in a long-term increase in ridership of 4.7%, 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 that may include changing demographics, population, or socio-economic factors. Changes in service are also found to affect this trend. Decreasing three routes in June 1996 had a negative effect, while adding Saturday service and Friday night routes in June 2004 had a positive impact. Cancelling the Friday night routes a few months later did not have a significant effect on ridership. The downtown shuttle, while it was in service, had a positive effect. The effects of creating new routes with fewer transfers in April 2002 and the minor routes changes in January 2006 were not found to be statistically significant. The impact of decreasing routes in February 1998 was unexpectedly found to be positive.

Table 8.3 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

9. PANEL DATA MODEL

Another approach to estimate the effect of gas prices on bus ridership is to use a panel data model that combines time series data for different transit systems. To this end, an econometric model is developed using ridership data from the National Transit Database. The model uses panel data for 11 transit systems over a period of 10 years, from 1997-2006. A pooling technique, the process of combining cross-section and time series data, is used in the analysis. The transit systems included are those previously shown in Table 2.2, whose ridership numbers were illustrated in Figure 2.4. The Logan, UT system was eventually removed from the model due to a lack of data for some variables. The model estimates ridership for these systems as a function of gas price, service quantity, fares, socio-economic factors, a trend variable, and various dummy variables as follows:

3) $R_{it} = \mathrm{f}(PG_{it}, QS_{it}, F_{it}, LF_{it}, U_{it}, UPASS_{it}, NDSUD_{it}, GF04_{it}, TR_{it})$,

where R_{it} = ridership for system *i* in year *t*,
PG_{it} = price of gas for system *i*'s region in year *t*,
QS_{it} = quantity of service for system *i* in year *t*,
F_{it} = fares for system *i* in year t,
LF_{it} = size of labor force for system *i*'s service area in year *t*,
U_{it} = unemployment rate for system *i*'s service area in year *t*,
$UPASS_{it}$ = UPASS dummy variable for Fargo-Moorhead,
$NDSUD_{it}$ = NDSU downtown dummy variable,
$GF04_{it}$ = Grand Forks dummy variable for 2004-06, and
TR_{it} = time trend.

The price of gas is expected to have a positive effect on ridership. The quantity of service should have a positive effect, as an increase in service coverage or frequency is expected to increase ridership. Fares are expected to have a negative effect on ridership. Two socio-economic/demographic variables are included in the model: labor force and unemployment. The size of the labor force is expected to have a positive effect because it is an indicator of the size of the market area the transit system serves. Unemployment, on the other hand, should have a negative effect. An increase in the rate of unemployment is expected to negatively influence ridership because it causes a reduction in commuter travel and, consequently, demand for transit.

As discussed previously, the Fargo-Moorhead Metro Area Transit (MAT) started a U-Pass program in 2001-02 that allowed college students, and faculty and staff for some colleges, to ride free. Therefore, a dummy variable is included in the model equal to 1 during the period in which this program has been in place and 0 otherwise. It is expected that the U-Pass program has a positive impact on ridership for this transit system. Another dummy variable specific to MAT is added to account for the opening of an NDSU building in downtown Fargo in 2004, which created a demand for students to travel between campus and the building. One dummy variable is included for Cities Area Transit (CAT) in Grand Forks to account for the apparent structural change in ridership that occurred between 2003 and 2004. Ridership dropped substantially between these two years. This dummy variable will test for structural change.

Finally, a trend variable is included to account for trends in ridership that are not accounted for by the other variables. Since it is likely that the trends will vary between transit systems, the model is revised to include interactions between the trend variable and dummy variables for the transit systems, which allows for different trends to be estimated for each transit system. The model is further revised to have the U-Pass dummy variable interact with the trend since the impact of the U-Pass program is likely to have increased over time. The reason for this is that the U-Pass included just North Dakota State University in the first year, but then additional colleges and universities, which also allowed faculty and staff to ride free, were added to the program in each of the next three years.

The model is estimated using a one-way fixed effects approach, which includes cross section dummy variables. There are 10 dummy variables for the 11 transit systems. Including these dummy variables can capture some of the differences between the transit systems, or the cities where these systems are located, which are not accounted for by the other variables in the model. For example, differences in population densities, student populations, attitudes toward transit, service quality, etc. may differ between cities, and these cross section dummy variables may capture some of these differences. Time series dummy variables are not included (that is, dummy variables for years) because they add no explanatory power to the model. The trend variable captures changes over time that are not accounted for by the other variables. The model is estimated in a double-log functional form as follows:

$$\text{4)} \quad \ln R_{it} = \alpha_0 + \alpha_1 \ln PG_{it} + \alpha_2 \ln QS_{it} + \alpha_3 \ln F_{it} + \alpha_4 \ln LF_{it} + \alpha_5 \ln U_{it} + \alpha_6 UPASS{*}TR_{it} + \alpha_7 NDSUD_{it} + \alpha_8 GF04_{it} + \alpha_9 TR_{it} + \alpha_{10} CS1_{it}{*}TR_{it} + \ldots + \alpha_{19} CS10_{it}{*}TR_{it} + \alpha_{20} CS1_{it} + \ldots + \alpha_{29} CS10_{it} + \varepsilon_{it} .$$

One advantage of this model over the previous ones is that it includes specific data for service quantity, fares, and some socio-economic factors. It does not include dynamics, but it uses annual data, and most of the previous results indicated that the full effect of a change in gas price is observed within one year. While elasticities have been found to vary between cities, this model provides an average elasticity for a larger sample of small urban transit systems.

9.1 Data

The model uses annual data for 1997-2006 for 11 transit agencies. Ridership and service quantity data were obtained from the National Transit Database. Ridership is measured as the total unlinked passenger trips for the fixed route system. Service quantity is measured as the number of vehicle revenue miles for the fixed route system. This database does not include fare data, but it does include fare revenue. Fare revenue for the fixed route system is divided by ridership to obtain the fare received per unlinked passenger trip, which is used as a proxy for fares. Labor force and unemployment data were obtained from the Department of Labor's Bureau of Labor Statistics. Information on Fargo-Moorhead's U-Pass program and NDSU downtown were gathered from the Fargo-Moorhead Metropolitan Council of Governments.

9.2 Results

The results are shown in Table 9.1. The variables all have the expected effects, and all are statistically significant except for the size of the labor force. Since a double-log model is estimated, the estimated coefficients are elasticities. The gas price elasticity is found to be 0.12, which indicates that a 10% increase in gas price leads to a 1.2% increase in ridership. This result is similar to previous estimates reported in Table 5.1.

The elasticities for service miles and fares are 0.24 and -0.45, respectively. This fare elasticity is similar to estimates from other studies for the short- or medium-run. The labor force variable is insignificant, though it is possible that the cross section dummy variables account for the differences in population between the cities. The unemployment rate is found to have a negative impact on ridership, with an elasticity of -0.13.

Table 9.1 Results from the Panel Data Model

Explanatory Variable	Estimate	t-value
Intercept	7.980	1.06
Gas price	0.119	2.11**
Service miles	0.243	2.86**
Fare	-0.446	-5.73**
Labor force	0.004	0.01
Unemployment	-0.128	-2.50**
U-Pass*trend	0.067	1.75*
NDSU downtown	0.203	2.95**
Grand Forks 2004-06	-0.768	-8.72**
Trend	-0.033	-2.06**
Duluth*Trend	0.031	1.93*
St. Cloud*Trend	0.060	4.80**
Rochester*Trend	0.079	6.37**
Sioux Falls*Trend	0.060	5.54**
Fargo-Mhd*Trend	0.034	1.83*
Grand Forks*Trend	0.056	2.88**
Missoula*Trend	0.048	4.60**
Great Falls*Trend	0.030	2.19**
Rapid City*Trend	0.026	2.50**
Cheyenne*Trend	0.051	4.28**
CS1 (Duluth)	2.69	2.98**
CS2 (St. Cloud)	1.88	3.00**
CS3 (Rochester)	1.91	3.38**
CS4 (Sioux Falls)	1.17	1.74*
CS5 (Fargo-Mhd)	1.36	2.07**
CS6 (Billings)	1.36	3.18**
CS7 (Grand Forks)	1.13	4.32**
CS8 (Missoula)	1.25	6.52**
CS9 (Great Falls)	0.97	13.59**
CS10 (Rapid City)	0.46	1.59

*denotes significance at the 10% level

**denotes significance at the 5% level

The dummy variables for Fargo-Moorhead and Grand Forks are all highly significant, as are the trend variables. The trends also vary by city. Rochester, St. Cloud, and Sioux Falls exhibit the greatest positive trends in ridership, after accounting for the other variables, while Billings shows a negative trend after accounting for the other variables. The estimates for the cross section dummy variables are highest for Duluth, followed by St. Cloud and Rochester, indicating that ridership is higher in these cities due to other factors. These other factors could potentially include population, population density, service quality, income levels, or automobile ownership levels.

10. CHANGES IN FARE REVENUE AND FUEL EXPENSES

Gas prices in the midwest and mountain states increased by 12-20% per year from 2002 to 2006, and by 10% in 2007. With an estimated elasticity of 0.12, these gas price increases would have led to increases in ridership of approximately 1.5-2.5% per year during this period. The actual average annual increase in fare revenues for the small urban transit systems analyzed in this study during the 2002-2006 period ranged from 1.4% for the Missoula Urban Transportation District to 12.2% for Fargo-Moorhead Metro Area Transit (data for the City of Rochester Public Transportation were not available) (Table 10.1). The average systems experienced an increase in fare revenue of approximately 5-6% per year. The increase in gas prices, therefore, could explain as much as a third of the growth in fare revenues during this period.

Table 10.1 Fare Revenue for Select Small Urban Transit Systems, 2002-2006

	2002	2003	2004	2005	2006	Annual growth rate
	----------------thousand dollars----------------					
Duluth Transit Authority	1,418	1,400	1,564	1,668	1,904	7.7%
St. Cloud Metropolitan Transit Commission	613	606	598	705	779	6.2%
Sioux Falls Transit	326	321	352	377	403	5.4%
Fargo-Moorhead Metro Area Transit	367	399	412	468	582	12.2%
Billings Metropolitan Transit	171	184	181	185	208	4.9%
Cities Area Transit	133	140	112	132	144	2.1%
Missoula Urban Transportation District	313	305	302	323	332	1.4%
Great Falls Transit District	142	157	151	151	171	4.7%
Rapid Transit System	103	97	106	115	123	4.5%
The City of Cheyenne Transit Program	78	75	65	81	87	2.9%

Source: National Transit Database

While the results show that the higher gas prices have some positive impact on bus ridership, the increase in fare revenues has not been nearly enough to cover the growth in fuel expenses for these transit systems. Table 10.2 shows the increase in fuel and lube expenses for many of the transit systems analyzed in this study for 2002 through 2006, as reported in the National Transit Database. During this five-year period, these transit systems experienced average annual growth rates in fuel and lube expenses ranging from 18% to as high as 40%. Since the number of service miles did not change significantly for most of these transit agencies (some, in fact, reduced their service miles), nearly all of the increase in fuel expenses can be explained by higher fuel costs. The Rapid Transit System and the Cheyenne Transit Program did increase service miles by an average of 5-7% per year, but this is substantially lower than the 25-29% increase in fuel and lube expenses.

As these expenses rise, they consume a larger portion of the transit system's total budget. In 2002, fuel and lube expenses accounted for about 5-7% of the total operating expenses for most of these transit agencies, but by 2006, that share had roughly doubled to approximately 10-15% (Table 10.3). These percentages have most likely increased further as fuel prices have continued to rise in 2007 and 2008. As shown in Table 10.4, the growth in fare revenues has not been enough to cover the higher fuel expenses.

Table 10.2 Fuel and Lube Expenses for Select Small Urban Transit Systems, 2002-2006

	2002	2003	2004	2005	2006	Annual growth rate
	----------------thousand dollars----------------					
Duluth Transit Authority	403	425	523	758	900	22.2%
St. Cloud Metropolitan Transit Commission	214	247	272	407	556	26.9%
Sioux Falls Transit	117	140	186	272		32.3%
Fargo-Moorhead Metro Area Transit	129	171	230	357	500	40.3%
Billings Metropolitan Transit	134	156	172	239	316	24.0%
Cities Area Transit	85	149	162	184	205	24.7%
Missoula Urban Transportation District	121	114	138	160	234	17.8%
Great Falls Transit District	111	126	94	185	254	23.1%
Rapid Transit System	24	32	36	59	67	29.2%
The City of Cheyenne Transit Program	45	42	45	73	109	25.0%

Source: National Transit Database

Table 10.3 Fuel and Lube Expenses as a Percentage of Total Operating Expenses, 2002-2006

	2002	2003	2004	2005	2006
	---------------------------%----------------------------				
Duluth Transit Authority	4.4	4.7	5.9	7.9	9.2
St. Cloud Metropolitan Transit Commission	6.7	7.1	7.2	10.0	12.2
Sioux Falls Transit	4.9	5.4	6.9	9.7	
Fargo-Moorhead Metro Area Transit	5.1	6.4	7.8	11.4	13.8
Billings Metropolitan Transit	5.2	6.0	6.4	8.4	11.1
Cities Area Transit	7.0	12.2	12.6	14.3	14.6
Missoula Urban Transportation District	6.3	5.5	6.2	7.1	9.5
Great Falls Transit District	6.3	7.1	6.3	9.8	13.0
Rapid Transit System	5.6	6.8	7.2	9.9	11.7
The City of Cheyenne Transit Program	9.9	7.5	8.0	11.8	15.6

Source: National Transit Database

Table 10.4 Comparison of Fare Revenue and Fuel Expense Increases from 2002 to 2006

	Increase from 2002 to 2006		
	Fare Revenue	Fuel & Lube Expenses	Difference
	------------thousand dollars------------		
Duluth Transit Authority	487	497	-10
St. Cloud Metropolitan Transit Commission	166	342	-176
Sioux Falls Transit	76	154	-78
Fargo-Moorhead Metro Area Transit	215	371	-156
Billings Metropolitan Transit	36	182	-146
Cities Area Transit	12	120	-109
Missoula Urban Transportation District	19	113	-94
Great Falls Transit District	29	143	-115
Rapid Transit System	20	43	-23
The City of Cheyenne Transit Program	9	65	-55

11. SUMMARY AND CONCLUSIONS

Rising fuel costs have been a major concern in recent years. After being relatively stable for much of the 1990s, gas prices have roughly tripled over the last decade. The average price of a gallon of gasoline in the Midwest rose from $1.36 in 2002 to $2.82 in 2007, and it continues to increase in 2008. This climb is especially concerning to those in the transit industry, as it is causing an increase in operating expenses. On the other hand, it could have some positive effects as the increased cost of operating an automobile may lead some motorists to switch to public transportation.

In recent years, public transportation has benefited from an increase in ridership. This increase has been generally true for transit systems of all types, whether they be rail, bus, large-city operations, or small-city operations. A number of small urban transit systems in the upper midwest and mountain states have experienced increases in ridership over the last decade. The correlation between increasing gas prices and increasing transit ridership across the United States has led many observers to link the two together, suggesting that more and more motorists are opting for public transportation to avoid the high cost of gasoline. However, few studies have been conducted to analyze this relationship.

The studies that have been conducted suggest that demand for transit with respect to gas price is fairly inelastic, meaning that the change in ridership due to changes in gas prices is rather small. The elasticities reported in the literature vary quite a bit, though. Most estimates lie somewhere between 0.05 and 0.40, meaning that a 1% increase in gas price would lead to an increase in transit ridership of about 0.05-0.40%. This study expands upon the previous research by allowing for dynamics so that both short-run and longer-run elasticities can be estimated, by analyzing data for specific transit systems, and by concentrating on small urban and rural transit systems of the upper midwest and mountain states. 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 is 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. These elasticities are similar to previous estimates from other studies. 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 are 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 means that a 10% increase in gas price would result in a 2.2% increase in ridership. This result is similar to the 0.16 elasticity estimated for medium-small cities. CCRT operates two long-distance commuter routes from rural areas to the Fargo metro area. The results for the Detroit Lakes CCRT commuter route indicate an elasticity of approximately 0.5, and the estimate for the Barnesville commuter route is even higher than that, but in this case, the result is unreliable due to inadequate data. 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 fairly slow, but after 18 months, a long-run elasticity of 0.47 is estimated, indicating that a 10% increase in gas price results in a long-term increase in ridership of 4.7%. The slow response is similar to that 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. For example, while the estimates indicate that gas prices have a significant positive impact on CCRT ridership, ridership totals for the transit agency actually dropped substantially during the study period due to a decrease in service. Other contributing factors can explain much of the increase in ridership in Fargo and Cheyenne, such as the implementation of a U-Pass program in Fargo or general long-term trends favoring transit in Cheyenne.

Another approach to estimate the effect of gas prices on bus ridership is to use a panel data model that combines time series data for different transit systems. Such a model was developed using data for 11 small urban transit systems from the upper Midwest and mountain states over a period of 10 years, from 1997-2006. A pooling technique, the process of combining cross-section and time series data, is used in the analysis. One advantage of this model over the previous ones is that it includes specific data for service quantity, fares, and some socio-economic factors such as unemployment. It does not include dynamics, but it uses annual data, and most of the previous results indicated that the full effect of a change in gas price is observed within one year. While elasticities have been found to vary between cities, this model provides an average elasticity for a larger sample of small urban transit systems. The gas price elasticity is found to be 0.12, which indicates that a 10% increase in gas price leads to a 1.2% increase in ridership. Service miles, fares, the unemployment rate, and trend variables are also found to be important.

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.

Future research could be conducted to determine if the elasticities change as gas prices increase. The models in this study use data through 2006 or 2007, and one cannot necessarily assume that motorists will continue responding to gas price increases the same way they have previously. 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. Storchmann (2001), for example, found that ridership is most likely to increase by commuters during peak demand periods, so it is possible that ridership increases could lead to further cost increases for transit agencies since they may need to increase services to meet the demand. An increase in rush hour demand would create a need for more service, and Storchmann argued that it is more important to analyze marginal costs and marginal revenues to determine the effect of increased passengers. Finally, more research could be conducted to help transit systems manage continually increasing fuel costs and the associated uncertainty.

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