

THE CROSS ELASTICITY BETWEEN GASOLINE PRICES AND TRANSIT USE: EVIDENCE FROM CHICAGO

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Abstract

This paper calculates the cross elasticity between the price of gasoline and transit ridership in Chicago using monthly data for the period between January 1999 and December 2010. Separate estimations are conducted for city heavy rail, city bus, commuter rail and suburban bus services. A 12-month difference model is used to overcome seasonality. The paper finds that the cross elasticities when gas prices were less than \$3 a gallon were small, with a magnitude of less than 0.05. When prices exceeded \$3 a gallon, the elasticity was larger, in the range of 0.12-0.14, for the rail modes. In the summer of 2008 when prices exceeded \$4 a gallon, there was considerable responsiveness with elasticities of 0.28-0.30 for city and suburban bus, and 0.37 for commuter rail. These values are similar to, or even larger than, those found during the oil crises of the 1970s and early 1980s.

Keywords: gasoline prices, transit ridership, cross elasticity, Chicago

Research Highlights

- Estimates cross elasticity between gas prices and transit use in Chicago 1999-2010
- When gas prices were less than \$3 a gallon, cross elasticities were small
- Elasticity increased to 0.12-0.14 for rail-based modes when gas prices exceeded \$3
- Elasticities were in the 0.28-0.38 range when gas prices exceeded \$4
- These latter elasticities are similar to, or larger than, those found in the 1970s

1. Introduction

After two decades of declining in real terms, the price of gasoline has been increasing since the turn of the century. In the summers of 2007 and 2008 the price, adjusted for inflation, exceeded the previous peak price in March 1981.¹ As a result, the American Public Transportation Association (2010) reports that national transit ridership in 2008 was the highest it had been since 1956 (albeit that the United States population has increased by 80% in the interim, and the 1950s transit data did not include riders on commuter railroads). There has led to a renewed interest in estimating the cross-price elasticity between gasoline prices and transit ridership. This paper adds to the growing literature by using monthly data from 1999 to 2010 for the Chicago metropolitan region. The analysis is able to differentiate between the effects on city bus, city rail, suburban bus and suburban commuter rail ridership.

2. Literature Review

2.1 Aggregate Studies

A recent meta-analysis of the transit demand literature reports that the cross-price elasticity in countries with a generally low transit market share is approximately 0.2 in the short run and about 0.5 in the longer run (Holmgren, 2010). However, there is considerable variation around these midpoint values. In this review we will generally confined ourselves to studies that analyzed the larger cities in the United States.² A summary of the prior literature is given in table 1. Only elasticity estimates that are statistically significant from zero are shown. The elasticities are categorized by mode (bus, light rail, heavy rail/subway and commuter rail), time period and methodology.

Methodologically, the studies fall into three broad types. The first type use simple techniques such as univariate regression, correlation analysis, or comparative statics comparisons. The second type use multivariate ordinary least squares regressions. Some of these studies use logarithmic transformations for both the dependent and explanatory variables resulting in a constant elasticity value at all of the points along the function. Others do not use a double logarithmic transformation, and consequently the value of the elasticity will vary. Typically these studies report the value of the elasticity at the mean values for the explanatory variables.

The final type of study uses two-stage least squares (2SLS) regressions. The argument for doing so is that the price of oil not only factors into the demand for public transit but also into the cost function as well. While increased oil prices might encourage some auto drivers to switch to transit, the increased costs of providing transit will prompt the transit agency to increase fares and/or reduce service levels so as to meet their budget. Increased fares and reduced service will depress ridership. Only one previous study, Kemp (1981), has explicitly dealt with this issue by using 2SLS estimation. The more typical response is to argue that using

¹ Of course, average fleet fuel efficiency has improved, which makes comparisons over time more difficult.

² A large city is defined as having a population of 500,000 or more within the Metropolitan Statistical Area boundary. For a more extensive international review the reader is directed to Currie and Phung (2007).

monthly data reduces potential simultaneity problems as gas prices fluctuate from month to month, whereas transit fares and transit supply change only periodically.

With a few exceptions, the dependent variable used is total ridership for the mode, with ridership measured by boardings in the literature from the 1970s and by unlinked passenger trips in more recent times.³ Explanatory variables include, in addition to the price of gasoline, transit price, transit supply, the state of the macroeconomy, seasonality, time trends, and various other local idiosyncratic occurrences. Table 2 lists the explanatory variables employed in prior analyses.

Most estimated relationships are “instantaneous.” By that we mean that the estimated transit ridership effects occur in the same month that the gasoline price changed. While some travelers might be in a position to make a modal choice on a daily basis, for many others the choice is more complicated. Goodwin (1992) explains that many travelers can only reoptimize their modal choice at discrete points in time when, for example, they change residential location and/or employment. Blanchard (2009) tested the effect of introducing lagged values of the gas price. He found that the inclusion of the lagged prices did not improve the predictive powers of his estimated equations. In contrast, Yanmaz-Tuzel and Ozbay (2010) did find statistically significant positive effects from using medium run lags in the range of two to four months.

Authors in the 1970s and early 1980s found elasticities for bus services to be in the range of 0.17 to 0.29. There were a couple of more responsive outliers. The estimates for rail systems indicated less sensitivity, and were in the range of 0.08 to 0.11. However, the sample size is just two. The reasonably extensive literature from the 2000s has generally found smaller elasticities. In part, the greater responsiveness in the earlier period may have been due to restrictions in the availability of gasoline at certain times. In contrast, there has not been *nationwide* shortages, queuing or rationing in the past decade.

Perhaps the most comprehensive recent analysis is an undergraduate honors thesis by Blanchard (2009). Using a panel dataset of all transit agencies and monthly data for 2002 through August 2008, he estimated an elasticity of 0.08-0.10 for bus services, commuter rail and light rail. The relationship for heavy rail systems was close to zero and statistically insignificant. Blanchard also conducted regressions on individual cities for the rail modes and found considerable city-to-city variation, but most were in the range of 0.10 to 0.20. As reported in table 1, other city-specific studies have generally found similar results.

Another recent comprehensive analysis is by Lane (2010) who estimated linear regressions for ten metropolitan areas. However, many of his city-specific estimates were statistical insignificant. Some of his results support the city specific findings of Blanchard but some are at odds with Blanchard’s findings. With the exception of an outlier value of 0.43 for rail service in Denver (which Blanchard also detected), elasticities were again in the 0.10 to 0.20 range.

³ Exception are Bates (1981) who uses data on linked trips, Kemp (1981) who uses a panel of monthly data for individual routes and measures ridership as boardings by passengers who do not transfer, and Voith (1991) who uses a panel dataset of boardings at individual rail stations

2.2 Disaggregate Studies

This study is an aggregate demand analysis. Aggregate analysis has advantages and disadvantages. The advantage is its simplicity and its suitability to analyze fluctuations over time in gasoline prices. The disadvantage is that unlike disaggregate demand studies (Ortúzar and Willumsen, 2011) it does not give insights into which types of people may switch modes, and their decision making process.⁴

A review of disaggregate models in Europe by de Jong and Gunn (2001) reports elasticities in the 0.10 to 0.20 range based on Dutch and Italian national models, with higher values around 0.38 for an integrated land use and transportation model of the Brussels metropolitan region in Belgium. A much higher value of 0.7 was found by Frondel and Vance (2011) from a German annual household panel mobility survey for the years 1996 to 2007. A land-use and transportation model of the metropolitan Chicago region using data from the year 2000 does not explicitly report a cross-elasticity value, but reports that 43% of the estimated own-price elasticity of gasoline was due to drivers switching to transit (Anas and Hiramatsu, 2012).

3. Data

3.1. Transit in Chicago

The Chicago metropolitan area includes the City of Chicago with a population of 2.7 million, an inner ring of suburbs with a population of 2.5 million, and an additional 3.1 million residents in the outer suburbs and exurbs. A Regional Transit Authority (RTA) has taxing powers over the entire region. The RTA is the parent agency to three separate operating companies. The Chicago Transit Authority (CTA) provides bus and heavy rail elevated and subway train service in the City and inner suburbs with a fleet of 1,700 buses and 1,000 railcars operating on eight routes. We will refer to these modes as city bus and city rail respectively. A commuter rail agency (using the marketing name “Metra”) operates eleven radial routes linking all parts of the metropolitan area to downtown Chicago. A suburban bus agency (“Pace”) operates 500 buses on regular routes serving primarily the inner suburbs, often connecting with CTA rail service. Pace also provides service in the outlying areas particularly in four older satellite towns that have been subsumed in the metropolitan area.

3.2 Transit Ridership

Data were obtained from the RTA’s “Regional Transportation Asset Management System” (RTAMS) data warehouse at <http://www.rtams.org>. The origin of the CTA data is a CTA publication “Monthly Ridership Report.” For the bus system, ridership is measured as boardings, which corresponds to “unlinked trips.” The CTA rail system ridership measure is a

⁴ It would be possible using the data sources used in this paper to construct a panel dataset for each route within each mode (and even by station for rail modes) to give insights into how the cross-price elasticity may vary depending on the demographics of the neighborhoods that individual routes pass through or individual stations serve. For such an analysis in Melbourne, Australia see Currie and Phung (2008).

count of passengers entering stations. This does not correspond with unlinked trips as it does not count any free cross-platform interchange onto another rail line as a separate trip.⁵ The origin of Metra's data is their monthly "Commuter Rail System Ridership Trends" report. Metra bases their ridership count on ticket sales data.⁶ Pace ridership, like CTA bus, is measured by boardings on regular routes.⁷

A complication is that from March 17, 2008 the State of Illinois mandated that senior citizens could ride for free.⁸ Previously they could ride for half price, but this required obtaining a special identification card. Because seniors still had to obtain the special identification card, and there was a backlog in processing them, the full effects of the program were not apparent for a couple of months. In addition, low-income people with disabilities were allowed to ride free from October 24, 2008. Previously, they were also entitled to reduced fare rides.

The effect of these programs has been removed by subtracting the number of newly generated trips from the ridership totals for each month from April 2008. The generated ridership is calculated as the number of free ride tickets less the decline in reduced fare rides.⁹ These data are obtained from a special report commissioned by the RTA (DiJohn et al., 2010).

Ridership data for each of the modes are plotted on the left-hand axis of figure 1. There has generally been an upward trend in ridership for city bus, city rail and commuter rail, and a constant to slightly declining trend for suburban bus service. In addition, there is a readily apparent seasonal variation across the year.

3.3 Price of Gasoline

The gasoline price is the average price per (U.S.) gallon for self-service unleaded gasoline in Cook County, which encompasses Chicago and the inner suburbs. (The price in the outer suburban counties is typically about \$0.10 below the Cook County price.) The source is the American Automobile Association (AAA)-Chicago Motor Club that has, for almost forty years, issued a monthly press release containing the data. In recent times, the data are obtained by the AAA from two companies, Oil Price Information Service (OPIS) and Wright Express, both of whom analyze credit card transactions at retail stations.

⁵ The data in RTAMS is incorrect for January 2008 to April 2009 because it includes these cross-platform transfers. The correct data were obtained from the original CTA publication.

⁶ As with all data on Metra, we have excluded the "South Shore Line" which is operated by the Northern Indiana Commuter Transportation District.

⁷ Total monthly boardings are only shown in RTAMS for Pace from January 2003. The 1999-2002 data were obtained from a route-by-route listing within the RTAMS database. Pace data only includes regular route service, and excludes their van pool operation and paratransit demand response service to disabled riders.

⁸ Political controversy led to a revision in the program from September 1, 2011. Now only low income seniors can ride for free. All other seniors are eligible for reduced price rides.

⁹ The reduction in reduced fare rides is calculated relative to the number of such rides in the months between April 2007 and March 2008. Children, higher-income disabled, seniors living outside the metropolitan Chicago region, and some other groups still qualified for reduced fare rides. To some extent, this calculation may be a slight overestimate of the number of new trips because there were some seniors who previously did not bother to obtain an identification card and paid full fare

The data are plotted on the right-hand axis of figure 1. There has been a generally upward trend in gasoline prices, with each summer from 2003 to 2008 having higher prices than the summer before. The financial collapse of autumn 2008 led to a dramatic decline in prices, but they resumed their upward trend in 2009 and 2010. Gas prices show a distinct seasonality with price increases in the spring and declines in the fall.

3.4 Transit Supply

Our measure of transit supply is the average daily revenue vehicle miles (revenue car miles for rail modes). The default data source is the United States Federal Transit Administration's National Transit Database (NTD) at <http://www.ntdprogram.gov>. Because the data is annual, each month in a given year will consequently have the same numerical value. For Metra the data source is its annual "Budgets and Programs Statement" rather than the NTD.

There has been a general expansion in transit service over the decade. The commuter rail agency has opened a number of extensions to its existing lines, and revenue car miles were 21% higher in 2010 than in 1999. The CTA generally added service in the early 2000s, but budgetary problems led to significant service cuts in January 2010. Comparing 2010 with 1999, rail car miles increased by 17% whereas bus miles declined by 7%. Pace service has been more consistent with 2% higher mileage in 2010 compared with 1999.

3.5 Transit Fares

Our measure of fares is the one-way one-ride cash fare. In reality the effective fare is less than this amount because some users qualify for reduced fares, and users can purchase multi-ride and transfer tickets.¹⁰ The CTA and Pace charge a flat fare. Metra has a graduated fare scale. Our measure is the one-way fare from zone E to downtown Chicago. This zone covers stations 20 to 25 miles from downtown Chicago, consistent with Metra's average journey length of 22.75 miles.¹¹

The CTA one-way fare was constant at \$1.50 for a decade until it rose to \$1.75 in January 2004. The rail system saw a price rise to \$2.00 in January 2006, and then the fare on both modes increased to \$2.25 in January 2009. The Metra one-way zone E fare was \$3.50 in 1999, rose to \$3.70 in July 2002, \$3.90 in February 2006, \$4.30 in March 2008, and \$4.50 in February 2010. Pace's fare was initially \$1.25, and rose to \$1.50 in January 2001, and \$1.75 in January 2009.

3.6 Unemployment Rate

To represent the state of the macroeconomy, we used the percentage monthly unemployment rate for the Chicago-Joliet-Naperville Metropolitan Statistical Area, as reported by the United States Bureau of Labor Statistics at <http://www.bls.gov>. These data are plotted on

¹⁰ Using data from the NTD, the ratio of the effective fare (calculated by dividing farebox revenue by unlinked trips) to the posted fare prior to changes in the pricing for seniors in 2008 is approximately 0.5 for CTA Bus, 0.6 for CTA Rail and Pace and 0.75 for Metra.

¹¹ Journey lengths have a lower quartile of approximately 15 miles and an upper quartile of approximately 28 miles.

the right-hand axis of figure 1. Unemployment rose during the recession of late 2001 and early 2002 and recovered slowly over the subsequent years. The financial crisis of autumn 2008 led to a dramatic and rapid increase that continued through 2009. Unemployment then started to decline in 2010.

4. Analytical Issues

4.1 Time Trend

As indicated in table 2, some previous authors have employed a time trend as an explanatory variable. A time trend was tried early in our research, but proved to be problematic. With the exception of the rapid drop in the price of gasoline during the financial crisis of autumn 2008, the general trend during the period has been upwards. In addition transit fares and service levels have also trended upwards. Consequently we found that the time trend captured nearly all of the variability in the regression at the expense of the other variables.

A similar problem occurred when the Consumer Price Index was used to convert the price of gasoline and the transit fare variables into their inflation-adjusted values. Because transit fares remained constant for long periods of time, and inflation has been growing at a small but relatively consistent rate of 2.1% per year, an inflation-adjusted transit price variable effectively became a time trend variable. Consequently, the variable seemed to be picking up a myriad of effects unrelated to the transit fare. As a result, we decided to use nominal prices for gasoline and transit rather than make an inflation adjustment. Clearly, this is less of an issue than it might have been in the late 1970s when inflation was very high.

4.2 Seasonality

Using monthly data requires the analyst to deal with the normal variation in ridership across the year. In Chicago there is 18% higher total ridership in the busiest month, October, than there is in the slowest month, February. In part the monthly variation is due to measurable features such as the number of days in the month, the occurrence of leap years, and the number of weekdays (as opposed to weekend days and public holidays) in a given month in a particular year. There are other, less readily measured, factors that explain the pattern of travel over the year including the climate, the school calendar, sports events, and public festivals.

There is also seasonality in gasoline prices. Prices, based on the monthly average between 1999 and 2010, are the lowest in January and February, and rise to be 24% higher between May and September, with a peak of 28% higher in June. The higher summer prices reflect the greater national demand for driving, and the switch to a more expensive summer blend for air quality purposes.

A plot of the average gas price and the average daily system ridership by month is shown in figure 2. For the purposes of this figure, a daily ridership is shown to correct for the different number of days in each month. In general the warmer weather months (indicated by a circle symbol) feature higher gas prices and higher transit ridership, whereas the colder weather months

(indicated by a diamond symbol) feature lower gas prices and lower ridership. When looking at first-order changes from month-to-month there are times of year, such as from September to October, when transit ridership increases and gas prices are declining, and other times of year, such as from May to June, when both gas prices and transit ridership are increasing.

Initially, in common with previous authors, we estimated an instantaneous relationship between gas prices and transit ridership using a fixed effects model to deal with seasonality. A constant elasticity (ln-ln relationship) regression was specified using a Prais-Winsten AR(1) “first difference” methodology to overcome problems of serial correlation of residuals and collinearity between the explanatory variables. Dummy variables for each month (excepting January) were included in the regression. However, the results were very unsatisfactory, and are not reported here for the sake of space. The primary reason for the poor results is the rather complicated exogenous trend over the year in gas prices and ridership that is apparent from figure 2. Consequently, we decided to estimate a 12-month difference model to overcome these strong seasonal effects.

4.3 Simultaneity

The NTD reports that in 2010 fuel and lubricants accounted for 7.5% of the operating cost of the CTA’s bus operation, 10.3% of Metra’s cost, and 8.9% of the cost of Pace’s regular route services.¹² Clearly the pressure of increasing oil prices may lead to fare increases and/or service contractions to balance budgets. Fares did increase multiple times during the 12 years, but service levels have generally been increasing.

The possibility of simultaneity in the 12-month difference equation prompted trying a 2SLS approach. In such an approach, transit fare and transit supply are assumed to be endogenously determined by the interaction of the demand function, the cost function and a budget constraint.¹³ The first stage in a 2SLS analysis involves estimating regressions for each of the endogenous variables with the exogenous variables that appear in one or more of the demand, cost or budget constraint functions as the explanatory variables. The second stage estimates the demand function using the fitted values for the endogenous variables that are obtained from the first stage regressions.

The demand functions estimated in this paper contain the following exogenous variables: gas prices, the unemployment rate, the proportion of weekdays in a month, and leap year Februaries. Of these, gas prices also appear in the cost function as an approximation of the factor price of diesel fuel. We added a second exogenous factor price, the price of labor.¹⁴ Finally, a variable measuring the exogenous budget constraint is included.¹⁵

¹² The CTA’s rail operations and one of Metra’s routes are electrified. Electricity in Northeastern Illinois is primarily generated by nuclear stations.

¹³ See Savage (2004) for a discussion of managerial objectives and the first order conditions for the choice of transit fares and service levels in Chicago.

¹⁴ This is calculated from annual data in the NTD as the total operating wages and benefits divided by the fulltime equivalent number of operating employees. Data is given for the CTA as a whole, so the same measure is used for both city bus and rail.

¹⁵ Subsidies in the Chicago region are based on a 1983 formula which allocates a set sales tax levy between the three operating agencies depending on where in the metropolitan area the sales tax is collected. The data were obtained

The results the 2SLS were very unsatisfactory, and the results are not shown for the sake of space. Not only were the cross-elasticity estimates poor, but the coefficients on some of the other variables took counterintuitive signs, and were inferior to the 12-month difference model. The cause of the problem can be found by looking at the first stage of the estimation. Increasing gas prices are predicted to *reduce* fares in all modes, with the effects highly statistically significant for the city modes. This is contrary to the evidence that the transit agencies responded by increasing fares in the past decade. There are other counter-intuitive results. For example, increased subsidies are associated with *reductions* in transit supply for three modes and an *increase* in fares for three modes.

While increasing fuel prices should have some role in fare increases and service reductions, there were other factors at work including new labor agreements, structural financing problems dating back to the 1980s, and increasing problems with pension liabilities and retirees' health care costs.

5. Estimation of a 12-month Difference Model

A constant elasticity (ln-ln relationship) regression was conducted on the monthly data from January 1999 to December 2010. The data for the estimations are obtained by subtracting the logarithm of the value of a variable in month $t-12$ from the logarithm of its value in month t . The dependent variable was total monthly modal ridership. The explanatory variables were the gasoline price, transit supply, transit fare, the unemployment rate, a dummy variable for a leap year February, and a variable measuring the proportion of the weekdays in the month.¹⁶

By plotting fitted and actual values for ridership, it became immediately apparent that the regressions were underpredicting the surge in ridership in the summers of 2007 and 2008 when gas prices were at their highest levels. Consequently, additional variables were introduced that would allow a larger cross elasticity as the gas price increased. The first exercise involved adding a variable that took the value of the logarithm of the gas price when the average price of regular gasoline was \$3 a gallon or more, and zero otherwise.¹⁷ We found that this variable generated statistically significant t statistics, and F tests were significant at the 5% level, for the city rail and commuter rail modes, but not for the two bus modes. However, plots of actual and predicted values still indicated that we were generally underpredicting the surge in ridership in the summer of 2008. Consequently we added an additional variable that took the value of the logarithm of the gas price when the average price of regular gasoline was \$4 a gallon or more,

from RTAMS and the annual reports of the RTA. Data is given for the CTA has a whole and is applied to both city bus and city rail. The agencies do have access to matching funds from the state legislature and from general discretionary funds, but these are in a ratio to the base sales tax allocation. Federal operating subsidies were negligible during this time period. The sales tax rate was raised by legislative action from April 1, 2008, and a real estate transfer tax levy established in the City of Chicago.

¹⁶ New Year's Day, Memorial Day, Independence Day, Labor Day, Thanksgiving Day and Christmas Day are treated as weekend days if they fall on a Monday through Friday.

¹⁷ The price exceeded \$3 for 31 of the 144 months in the dataset (September 2005, May to August 2006, April to September 2007, November 2007 to October 2008, April to June 2010, and July to December 2010).

and zero otherwise.¹⁸ This variable did not add to the predictive power of the city rail regression but was strongly statistically significant for city bus and commuter rail, and approached significance at the 5% level for suburban bus.

The final estimated equations are shown in table 3, and the resulting cross-price elasticity estimates are summarized in table 4. When gas is less than \$3 the estimated cross elasticities are small. City bus and suburban bus have estimates of 0.064 and 0.054 respectively, which are statistically different from zero. For the rail modes the estimates are 0.031 for city rail and 0.022 for commuter rail, which are statistically significant from zero at the 10% level.

When the price of gasoline rose into the \$3 to \$3.99 a gallon range, the cross elasticities became larger for the rail modes with a value of 0.122 for city rail and 0.143 for commuter rail. The elasticities in the summer of 2008 when gas exceeded \$4 a gallon are considerably larger for all of the modes except for city rail. The bus modes had similar elasticities with 0.283 in the city and 0.298 in the suburbs. Commuter rail's elasticity was much larger at 0.374. The greater responsiveness for commuter rail is perhaps not surprising as commuter rail is in a competitive marketplace with the automobile. Commuter rail's routes generally parallel the major radial highways, and it serves a suburban car owning clientele who decide to take the train for reasons of relative expense and to avoid peak period highway congestion. We are grateful to a reviewer who advances another explanation that the higher income suburbanites that frequent commuter rail have the financial means to choose between modes, whereas in the city users are often "locked into" certain modes in the short run for reasons of geography and personal finances and circumstance.

As to the other variables, we find the relationship between transit supply and ridership is statistically significant for all modes, except suburban bus, with elasticities of 0.17 for city rail, 0.29 for city bus and 0.57 for commuter rail. The calculated fare elasticities are statistically significant in suburban areas with magnitudes of -0.33 for suburban bus and -0.42 for commuter rail. In the city, the estimated elasticity is -0.11 for bus which is highly significant, and an insignificant positive value for rail. The latter result would seem to be associated with the 2009 fare increase when the fare for city bus was increased much more than for city rail, and would seem to have led to a mode shift in favor of rail.

The effect of unemployment on ridership is negative and statistically significant in suburban areas (especially for suburban bus), whereas there is not any statistical relationship in the city. This is perhaps not surprising given that suburban public transit is much more gear to and dependent on the journey to work, whereas transit in the city serves a diversity of journey purposes. The proportion of workdays in a month has, not surprisingly, a strong statistically significant effect for all modes, but the dummy variables representing the extra day in leap year February is not significant.

Tests were conducted to see if the elasticity when price decreased was different from that when price rose. Goodwin et al. (2004) discuss the fact that most gasoline own-price elasticity studies assume that there is a symmetry in that the same elasticity applies irrespective of whether gas prices are rising or falling, even though there may be some doubt as to whether or not this is

¹⁸ The price exceeded \$4 for 4 of the 144 months in the dataset (May to August 2008).

true. A variable that took the value of the 12-month change in the logarithm of the gas price when gas price decreased, and zero otherwise, was added to the equations.¹⁹ For city bus and commuter rail, the additional variable had highly insignificant t statistics, and F tests showed an insignificant improvement in predictive power. The additional variable was significant in both t and F tests for city rail and suburban bus, but the results had opposite signs. For city rail, a price decrease *reduced* the elasticity by 0.21 (effectively making the cross elasticity negative), and for suburban bus it *increased* it by 0.20. These latter results are not credible. The overall conclusion is that there is not strong evidence to suggest an asymmetry in elasticity between when gas prices are rising and falling.

6. Discussion and Conclusions

6.1 Methodological Issues

There are two main methodological conclusions. The first is that the use of monthly data leads to problems in sorting out the primarily exogenous cyclical patterns across the year from any mode shifts caused by the increasing world price of oil. Figure 2 shows that at some times of year gas prices are falling yet transit ridership is increasing, and other times of year both gas prices and transit ridership are increasing. We had the greatest success in using a 12-month difference model. Here one is comparing similar seasons. The resulting cross-price elasticity estimate inherently represents traveler responses over the medium rather than the short run.

The biggest drawback in moving to a 12-month difference equation is a concern about simultaneity. The use of 2SLS did not lead to an improvement in the estimation. Indeed, 2SLS lead to counterintuitive results. Despite the poor results in this analysis, one does need to be cognizant that because oil products represent 7-10% of transit costs, there will be a “rebound effect” on the mode split change when transit fares ultimately have to be increased or service levels curtailed.

6.2 Elasticity Estimates

One of the notable features of the previous literature is the apparent decline in the estimated magnitude of the cross elasticity from approximately 0.20 in the 1970s and early 1980s to 0.05 to 0.10 in decade after 2000. Our findings provide some insights that can reconcile the literature from these two periods.

In general we find that when gas prices were less than \$3 a gallon the cross elasticities were small and in the range of 0.02 to 0.05. When prices were in the \$3 to \$3.99 range per gallon, the elasticities increased for the rail-based modes to 0.12 to 0.14. We find some startlingly large elasticities during the May to August 2008 period when gas exceeded \$4 a

¹⁹ The 12-month difference in gas prices was negative for 31 of the 132 observations. Most of these observations are concentrated in the periods June 2001 to June 2002 and November 2008 to October 2009.

gallon. During that summer elasticities are estimated at 0.28-0.30 for bus services and 0.37 for commuter rail. These estimates are at or above the estimates from the 1970s and early 1980s.²⁰

Unlike during the oil crises of the 1970s, drivers in 2008 were not subject to rationing and queuing at gas stations, but there was an element of a “media frenzy” that may have led to a heightened response. It is likely that the surge in ridership included some people who decided to “try out” transit, and may well have ultimately decided to switch back. Because gas prices fell dramatically in the autumn months of 2008, it is unclear whether the increased ridership would have been sustained had gas prices remained high. After all, standing outside waiting for a bus or train is considerably less attractive in Chicago during the winter than it is in the summer months. In addition, had prices remained high for a lengthy period, some of the people who had switched from auto to transit may have found an alternative mode (such as a car pool) or changed their employment or found an alternative trip destination.

6.3 Policy Implications

The upward trend in oil prices in the past decade has given some hope to transit agencies that there will be a substantial mode shift in their favor. This analysis finds evidence to support such a hope in Chicago, a city that is generally well served by public transportation, particularly when prices exceeded \$4 a gallon in the summer of 2008. This dataset ends in December 2010. Prices in excess of \$4 returned for substantial periods in the summers of 2011 and 2012. Subsequent research will show whether the magnitude of the mode switching in the summer of 2008 was an aberration, or a predictor of the kinds of ridership gains if gas prices in this \$4 range become the “new normal.”

References

- Agthe, D.E. and Billings, R.B. (1978) ‘The impact of gasoline prices on urban bus ridership’, *Annals of Regional Science*, 12(1), pp. 90-96.
- American Public Transportation Association (2010) *Public Transportation Fact Book*, American Public Transportation Association, Washington D.C.
- Anas, A. and Hiramatsu, T. (2012) ‘The effect of the price of gasoline on the urban economy: from route choice to general equilibrium’, *Transportation Research Part A*, 46(6), pp. 855-873.
- Bates J.W. (1981) ‘A study of demand for transit use’. Ph.D. dissertation, College of Business, Georgia State University.
- Blanchard, C. (2009) ‘The impact of rising gasoline prices on U.S. public transit ridership’. Undergraduate honors thesis, Department of Economics, Duke University, Durham, North Carolina.

²⁰ Albeit that the earlier literature calculated responsiveness over an extended period and there may have been much larger short term ridership responses at the height of the oil crises in the winter of 1974 and the summer of 1979.

- Currie, G. and Phung, J. (2007) 'Transit ridership, auto gas prices, and world events: new drivers of change?' *Transportation Research Record: Journal of the Transportation Research Board*, 1992, pp. 3-10.
- Currie, G. and Phung, J. (2008) 'Understanding links between transit ridership and gasoline prices: evidence from the United States and Australia', *Transportation Research Record: Journal of the Transportation Research Board*, 2063, pp. 133-142.
- de Jong, G. and Gunn, H. (2001) 'Recent evidence on car cost and time elasticities of travel demand in Europe', *Journal of Transport Economics and Policy*, 35(2), pp. 137-160.
- DiJohn, J., Metaxatos, P., Sen, A., Pagano, M., Dirks, L. and Kokoshi, V. (2010) 'Analysis of the RTA Seniors and People with Disabilities Ride Free Programs'. Final Report to the Regional Transit Authority, Urban Transportation Center, University of Illinois at Chicago.
- Doi, M. and Allen, W.B. (1986) 'A time series analysis of monthly ridership for an urban rail rapid transit line', *Transportation*, 13(3), pp. 257-269.
- Fronzel, M. and Vance, C. (2011) 'Rarely enjoyed? a count data analysis of ridership in Germany's public transport', *Transport Policy*, 18(2), pp. 425-433.
- Gallucci, G. and Allen, J. (2009) 'Transit ridership models: present status and future needs'. Paper presented at the *Transport Chicago* Conference, June 2009.
- Goodwin, P.B. (1992) 'A review of new demand elasticities with special reference to short and long run effects of price changes', *Journal of Transport Economics and Policy*, 26(2), pp. 155-169.
- Goodwin, P., Dargay, J. and Hanly, M. (2004) 'Elasticities of road traffic and fuel consumption with respect to price and income: a review', *Transport Reviews*, 24(3), pp. 275-292.
- Haire, A.R. and Machemehl, R.B. (2007) 'Impact of rising fuel prices on U.S. transit ridership', *Transportation Research Record: Journal of the Transportation Research Board*, 1992, pp. 11-19.
- Haire, A.R. and Machemehl, R.B. (2010) 'Regional and modal variability in effects of gasoline prices on U.S. transit ridership', *Transportation Research Record: Journal of the Transportation Research Board*, 2144, pp. 20-27.
- Holmgren, J. (2007) 'Meta-analysis of public transport demand', *Transportation Research Part A: Policy and Practice*, 41(10), pp. 1021-1035.
- Kemp, M.A. (1981) 'Bus services in San Diego: a study of patronage growth in the mid-1970's'. Working Paper 1470-1, The Urban Institute, Washington, D.C.

- Lane, B.W. (2010) 'The relationship between recent gasoline price fluctuations and transit ridership in major U.S. cities', *Journal of Transport Geography*, 18(2), pp. 214-225.
- Maley, D. and Weinberger, R. (2009) 'Does gas price fuel transit ridership?', *Panorama* (The University of Pennsylvania School of Design), 20, pp. 17-21.
- Ortúzar, J and Willumsen, L.G. (2011) *Modelling Transport* (4th edition), Wiley, Chichester.
- Savage, I. (2004) 'Management objectives and the causes of mass transit deficits', *Transportation Research Part A: Policy and Practice*, 38(3), pp. 181-199.
- Voith, R. (1991) 'The long-run elasticity of demand for commuter rail transportation', *Journal of Urban Economics*, 30(3), pp. 360-372.
- Wang, G.H.K. and Skinner, D. (1984) 'Impact of fare and gasoline price changes on monthly transit ridership: empirical evidence from seven U.S. transit authorities', *Transportation Research B: Methodological*, 18(1), pp. 29-41.
- Yanmaz-Tuzel, O. and Ozbay, K. (2010) 'Impacts of gasoline prices on New Jersey Transit ridership', *Transportation Research Record: Journal of the Transportation Research Board*, 2144, pp. 52-61.

Table 1: Summary of statistically significant cross-price elasticities between gasoline prices and transit ridership in the United States

Source (Chronological order)	Data Range	Location	Bus	Light Rail	Heavy Rail	Commuter Rail	Methodology
Agathe & Billings (1978)	9/73-6/76	Tucson	0.42	-	-	-	ln-ln regression
Bates (1981)	1/70-12/79	Atlanta	0.23	-	-	-	ln-ln regression
Kemp (1981)	1/72-4/75	San Diego	0.29	-	-	-	Linear 2SLS regression
Wang & Skinner (1984)	1/73 – 12/80	Albany, New York	0.22	-	-	-	Linear regression
Wang & Skinner (1984)	1/70 – 12/79	Atlanta	0.22	-	-	-	Linear regression
Wang & Skinner (1984)	9/76 – 12/80	Des Moines	0.80	-	-	-	ln-ln regression
Wang & Skinner (1984)	3/76 – 3/80	Jacksonville	0.18	-	-	-	ln-ln regression
Wang & Skinner (1984)	1/72 – 10/80	New York City	0.17	-	0.08	-	ln-ln regression
Doi & Allen (1986)	1/78 – 7/84	Philadelphia (Lindenwold)	-	-	0.11	-	ln-ln regression
Voith (1991)	Fall 78 - Fall 86	Philadelphia	-	-	-	Unclear ^a	Autoregressive
Currie & Phung (2007)	1/98 – 12/05	National aggregate	0.00	0.28	0.08	-0.09	ln-ln regression
Haire & Machemehl (2007)	1/99 – 6/06	Dallas	0.54	0.11	-	0.49	Not a regression
Haire & Machemehl (2007)	1/99 – 6/06	Los Angeles	0.22	0.06	0.11	0.21	Not a regression
Haire & Machemehl (2007)	1/99 – 6/06	San Francisco	-	-	0.23	0.37	Not a regression
Haire & Machemehl (2007)	1/99 – 6/06	Washington, DC	0.31	-	0.40	-	Not a regression
Blanchard (2009)	1/02 – 8/08	Maximum of 218 individual systems	0.06	0.10	-	0.09	ln-ln regression
Blanchard (2009)	1/02 – 8/08	Individual systems serving population of 0.5m-2m	0.08	-	-	-	ln-ln regression
Blanchard (2009)	1/02 – 8/08	Individual system serving population > 2m	0.09	-	-	-	ln-ln regression
Blanchard (2009)	1/02 – 8/08	Boston	-	-	0.14	-	ln-ln regression
Blanchard (2009)	1/02 – 8/08	Chicago	-	-	0.09	-	ln-ln regression
Blanchard (2009)	1/02 – 8/08	Cleveland	-	-	-0.38	-	ln-ln regression
Blanchard (2009)	1/02 – 8/08	Dallas-Fort Worth	-	-	-	0.21	ln-ln regression
Blanchard (2009)	1/02 – 8/08	Denver	-	0.51	-	-	ln-ln regression
Blanchard (2009)	1/02 – 8/08	Los Angeles	-	-	-	0.13	ln-ln regression
Blanchard (2009)	1/02 – 8/08	Philadelphia	-	-	-	0.13	ln-ln regression
Blanchard (2009)	1/02 – 8/08	Portland, Oregon	-	0.21	-	-	ln-ln regression
Blanchard (2009)	1/02 – 8/08	San Diego	-	-	-	0.20	ln-ln regression
Blanchard (2009)	1/02 – 8/08	San Francisco	-	-	0.10	-	ln-ln regression
Blanchard (2009)	1/02 – 8/08	San Jose, California	-	0.23	-	-	ln-ln regression

Gallucci & Allen (2009)	1/03 – 12/08	Chicago	0.14				Not a regression
Maley & Weinberger (2009)	1/01 – 5/08	Philadelphia	0.12		0.22		Linear regression
Lane (2010)	1/03 – 4/08	Boston	-	0.16			Linear regression
Lane (2010)	1/02 – 4/08	Chicago	0.10	0.13			Linear regression
Lane (2010)	1/02 – 4/08	Denver	0.18	0.43			Linear regression
Yanmaz-Tuzel & Ozbay (2010)	9/04 – 8/06	New Jersey	0.12 (short run)				ln-ln regression
Yanmaz-Tuzel & Ozbay (2010)	9/03 – 8/07	New Jersey	0.18 (medium run)				ln-ln regression
Yanmaz-Tuzel & Ozbay (2010)	5/07 – 12/08	New Jersey	0.11 (short run)				ln-ln regression
Haire and Machemehl (2010)	1/02-12/07	Maximum of 254 individual systems	Unclear	-	Unclear	Unclear	Semi-ln regression

^a Unlike the rest of the literature, Voith's (1991) measure of driving costs included a whole range of variable auto costs including the cost of parking downtown. Because his paper does not indicate the proportion of the variable driving costs that are attributable to gasoline, we cannot compare his numerical results with the rest of the literature.

Table 2: Summary of explanatory variables employed in prior literature

Source	Explanatory Variable List (in addition to gas price)
Agathe & Billings (1978)	vehicle miles, school month dummy, energy crisis dummy
Bates (1981)	fare, vehicle miles, working days in month, school weeks in month, time trend
Kemp (1981)	fare, average speed, waiting time, service duration, stop spacing, route length, non-working days in month, school days, time trend, route dummies, oil shortage variable
Wang & Skinner (1984)	fare, vehicle miles, working days in month, time trend, oil embargo dummy, seasonal dummies, work stoppage dummies
Doi & Allen (1986)	fare, bridge tolls, seasonal dummies, station closure dummy
Voith (1991)	fare, service frequency, train speed, auto fixed and variable costs
Currie & Phung (2007)	monthly dummies
Haire & Machemehl (2007)	not a regression
Blanchard (2009)	vehicle miles, monthly dummies, yearly dummies
Gallucci & Allen (2009)	not a regression
Maley & Weinberger (2009)	seasonal dummies
Lane (2010)	vehicle miles, peak vehicle requirement, time trend, seasonal dummies
Yanmaz-Tuzel & Ozbay (2010)	fare, vehicle hours, regional employment, monthly dummies
Haire & Machemehl (2010)	fare, vehicle hours, peak vehicle requirement, weekdays in month

Table 3: Regression on the 12-month difference in logarithm of monthly transit ridership, with t statistics in parentheses

Variables are 12-month difference	City Rail (CTA Rail)	City Bus (CTA Bus)	Commuter Rail (Metra)	Suburban Bus (Pace)
Ln of gas prices	0.031 (1.90)	0.064 (4.25)	0.022 (1.62)	0.054 (2.61)
Ln of gas prices multiplied by dummy=1 if gas is more than \$3, 0 otherwise	0.090 (2.65)	-	0.121 (3.96)	-
Ln of gas prices multiplied by dummy=1 if gas is more than \$4 , 0 otherwise	-	0.219 (2.40)	0.231 (2.93)	0.244 (1.93)
Ln of average daily transit bus (car) miles	0.173 (1.99)	0.293 (4.99)	0.569 (6.45)	0.208 (0.62)
Ln of transit fare	0.038 (0.88)	-0.115 (2.76)	-0.419 (5.13)	-0.334 (3.26)
Ln of unemployment rate	-0.009 (0.54)	-0.005 (0.27)	-0.055 (4.12)	-0.149 (5.27)
Ln of the proportion of weekdays in month	0.385 (5.69)	0.363 (5.21)	0.329 (5.85)	0.516 (5.42)
Dummy variable for a leap-year February	0.024 (1.69)	0.022 (1.49)	-0.021 (1.74)	0.002 (0.12)
Observations	132	132	132	132
F statistic	9.04	13.85	24.79	28.13
Adjusted R squared	0.30	0.41	0.59	0.59

Table 4: Cross-price elasticity estimates between the price of gasoline and transit ridership from the 12-month difference equation

	City Rail (CTA Rail)	City Bus (CTA Bus)	Commuter Rail (Metra)	Suburban Bus (Pace)
Price below \$3/gallon	0.031	0.064	0.022	0.054
Price between \$3.00 and \$3.99/gallon	0.122		0.143	
Price above \$4/gallon		0.283	0.374	0.298

Fig 1: Monthly ridership by mode (left hand axis), unemployment rate and gas prices (right hand axis)

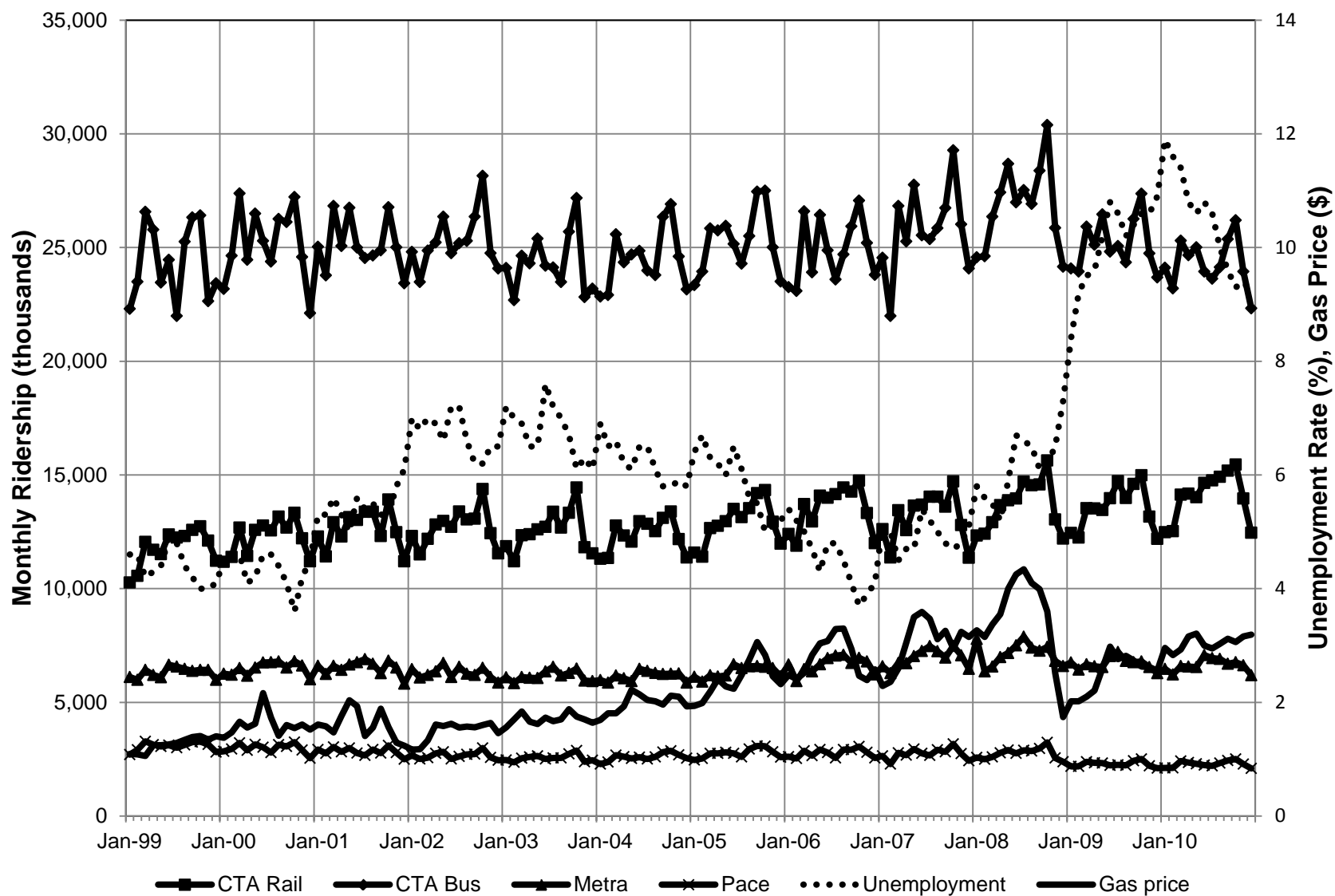


Fig 2: Average daily system ridership and average gas prices 1999-2010 by month

