The Effect of Gas Prices and Gas Taxes on Public Transportation Ridership

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Abstract

The cross-price elasticity of public transit ridership with respect to fuel prices is an important variable for policy makers to understand, especially as some areas consider taxes aimed at reducing the high carbon emissions associated with traditional vehicles. In this paper, I use panel data from 10 major American cities between 2006-2018 and estimate this elasticity to be 0.025, though I find significant variation between different modes of transportation and cities. I also investigate whether the entrance of Uber into these cities between 2010 and 2014 affected this elasticity, but I found the evidence for this to be inconclusive. Finally, previous research into this topic has not considered differences in the effect between gas tax changes and ordinary gas price changes, but there is theoretical and empirical evidence to suggest that the difference might be relevant. To address this, I consider evidence from all 50 states' gas tax rates and annual transit usage over time as well as a difference-in-differences regression around a 2008 Minnesota fuel tax increase. The evidence from these analyses is mixed, with the latter analysis indicating a significant impact in the effect of fuel taxes on transit ridership but not the former.

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1. Introduction

The effect of gas prices on public transportation is a topic of significant research and policy interest. Understanding how public transit demand is likely to respond to fuel price changes is important for urban planners looking to predict what levels of public transportation services are needed. Moreover, the cross-price elasticity speaks to the effectiveness of fuel taxes as a method to decrease car usage for environmental or safety reasons. As ridership of some modes of public transit has declined in many cities[1], some local governments have explored plans to raise gas taxes and even make public transit free[2]. If rising fuel prices cause many people to use public transportation instead, such taxes would be an effective policy measure. If, on the other hand, the effect was small, and most people do not change their habits, such taxes would be less useful.

Another reason for the relevance of the elasticity between gas prices and transit usage is that it speaks to the potential of avoiding decreases in economic activity due to, for example, environmentally oriented gas taxes. One might imagine that a large increase in gas prices could lead some consumers to limit their non-essential shopping trips or weaken local labor markets by discouraging longer commutes. A robust shift in transportation from private vehicles to public transit, on the other hand, could capture some of the environmental benefit of reducing carbon emissions without causing the same decrease in economic activity.

Intuitively, we would expect higher gas prices for private cars to lead to more usage of public transportation in lieu of cars, but it is not obvious how large this cross-price elasticity

[1] https://www.nytimes.com/interactive/2020/03/13/upshot/mystery-of-missing-bus-riders.html

[2] https://www.nytimes.com/2020/01/14/us/free-public-transit.html

should be. This question has generated a substantial empirical literature over the past 20 years as detailed data on transit usage and gas prices became widely available in the early 2000's. This prior research can be roughly classified into two groups, one of which uses data from a single city, state, or metropolitan area to understand the effects of gas price increases on transit in that area. These studies often limit themselves to large, exogenous increases in gas price to ensure that the estimates of the elasticity are not biased by confounding variables. The second strand involves looking at a broader geographic area, like panel data for many cities over time or aggregate time series data for an entire country, to better estimate the average effect of raising gas prices. These studies benefit from the additional information given by each area considered, but they may be more vulnerable to errors of excessive aggregation or confounding variables between areas and can obscure the considerable heterogeneity of the elasticity between areas. Almost all prior research does not distinguish between gas price increases caused by fuel tax hikes and by other reasons.

My research aims to combine the benefits of these approaches by estimating the elasticity of transit ridership with respect to gas prices using panel data from 10 major American cities between 2006 and 2018. I use standard techniques, discussed in more detail below, to estimate the average effect for cities, while also considering how the effect differs in different types of areas. Since most related studies only use data from 2010 and earlier, the inclusion of more recent data should help me better understand how the elasticity has been affected by recent transportation trends, such as the emergence of ride-hailing apps like Uber. With one specification, I consider directly whether Uber had an impact on the elasticity using data on the timing of Uber's entry into each city.

I also directly examine the possibility that the effect of gas taxes on transit usage may be different from the effect of gas price changes on transit usage. There are two reasons this could be the case. First, gas taxes may seem more salient. Drivers could see reporting on gas taxes in the news or television, while they may be unaware of daily gas price fluctuations. Second, gas taxes might seem more likely to be permanent. If we consider a model of transportation behavior with switching costs — such as the one proposed by Donna (2018) — a long-term increase in the price of driving would be more likely to compel people to switch from driving to transportation. Indeed, Li, Linn, and Muehlegger (2014) find that gas taxes are more likely than gas price increases to decrease gasoline consumption and vehicle miles travelled and increase consumption of fuel-efficient vehicles. This theoretical reasoning and related empirical evidence indicate that a similar phenomenon could exist between gas taxes and transit usage. Thus, I use state-level fuel tax data to analyze the effect of gas taxes on transit ridership. I adopt a similar framework to Li, Linn, and Muehlegger to identify the differences in effects driven by gas taxes and other changes in gas prices as well as a difference-in-differences design to analyze the impact of a substantial state fuel tax increase in Minnesota in 2008.

My analyses incorporate data from several sources. For data on transportation, I use the National Transit Database (NTD), which reports ridership data in terms of unlinked passenger trips (UPT) for every mode of transit in every major metropolitan area in the United States on a monthly basis. For data on gas prices, I use the United States Energy Information Administration (EIA), which provides monthly average gas prices in 10 major American cities and 9 states. Most states collect per-gallon excise taxes on gasoline, and the US Department of Transportation's Federal Highway Administration (FHA) provides information about each state's fuel tax on an annual basis. I collected some demographic control variables about each area like population, median household income, and age brackets from the American Communities Survey (ACS). For most of my regressions, I use data from 2006–2018.

For each of my regressions using city-level panel data, the dependent variable is the (natural) log of monthly public transit trips, sometimes disaggregated by mode of transit, for an area. The right-hand side of the regression equation consists of the log of average monthly per-gallon gas price, along with demographic controls and time and location fixed effects to limit the impact of confounding variables. The log-linear structure of the regressions allows for the coefficient on the gas price variable to be interpreted as the cross-price elasticity of transit usage with respect to gas price.

My first specification involves regressing the log of total monthly trips in each city on the log of average gas price along with demographic control variables and city and month fixed effects. I estimate a cross-price elasticity of 0.025 with a 95% confidence interval ranging from close to 0 to 0.037. I also find that the elasticity differs between modes of transit and tends to be higher for rail systems than bus systems and that the medium- and long-run elasticities may be larger than the short-run elasticities.

I then modify this regression in several ways to obtain further insight. I break the 10 cities into two categories consisting of those with highly developed public transit networks and those without. After pooling the data based on which category they fall in and running separate regressions for both pools, I find that cities with more developed transit networks tend to have a larger cross-price elasticity, suggesting that changes in gas prices may lead to more substitution with transit in areas where transit usage is already more common.

I also consider an instrumental variables approach where I regress the log of monthly trips in a city on the log of average gas prices in the state the city is located in. The idea behind this approach is to remove bias due to unobserved variables in a city that could cause an increase in demand for both gas and transit (for example, a large one-time conference or sporting event), but I obtain broadly similar results. I also find that the entry of Uber does not seem to be associated with a change in the elasticity, at least in the short run.

Then, I move to considering separately the role of gas taxes in affecting transit usage. Using data from all 50 states and a regression model similar to the one used by Li, Linn, and Muehlegger to tease apart the impact of gas prices and gas taxes separately, I do not find any evidence of gas taxes having an effect of transit usage. However, since gas taxes do not change frequently and the data is only available on an annual basis, these results may not be conclusive due to small sample size. On the other hand, I did find with a difference-in-differences estimator that a 2008 increase in the fuel tax in Minnesota led to more public transit usage than the average gas price otherwise would have predicted.

My results contribute to the long literature of factors determining transit ridership and can help inform debates about the effects of fuel taxes by estimating how transit ridership might respond to them. As more data becomes available, further research to continue to understand how the response of consumers to gas tax changes differs from gas price changes would be helpful. In particular, a raise in the federal gas tax, which has remained constant since 1993, would be an interesting policy experiment for analyzing substitution between private vehicles and public transportation.

The paper proceeds as follows. Section 2 lays out background information about the funding structure of public transportation and the demographics of transit riders before reviewing the prior literature relating to this topic. Section 3 describes the data sources used for the analysis and provides summary statistics. Section 4 outlines the methodology used to conduct the analysis, and Section 5 describes the results. Section 6 concludes and discusses limitations areas for future research.

2. Background and Literature Review

2.1 Fuel sources and cost structure of private vehicles and public transit

In this section, I will discuss the differences in how public transportation and private vehicles are financed and powered. The purpose of this section is to develop an understanding of how various effects (particularly changes in gasoline prices) might be expected to impact modes of transportation differently. This information can also help us understand the monetary impact of transitioning people between private and public transit, as well as other costs and benefits involved with shifts in transportation patterns.

The first important distinction between the cost structure of public and private transit is that a large portion of the cost of public transit is paid by the government. According to a 2015 report[3] from the US Department of Transportation's Federal Transit Administration (FTA), an average of just 33 percent of transit operating costs are paid by passenger fares, and another 12 percent are generated directly by the transit company (e.g. through advertising on trains and subways). In 2015, Congress allocated over $80 billion to transit funding throughout the country, though this represents just 2 percent of the US budget and was used to cover just 8 percent of transit operating costs. Local and state resources were used to cover the remaining 47 percent of operating costs.

Passenger fares and transit company revenue play an even smaller role in financing capital expenditures needed for transit services; combined they cover around 22 percent of these

[3] https://www.transit.dot.gov/sites/fta.dot.gov/files/docs/2015%20NTST.pdf

costs. Federal funding accounts for over 42 percent of capital costs, with state and local funding accounting for another 14 and 21 percent, respectively.

For private vehicles, the largest cost of ownership is depreciation of the vehicle's worth, contributing to 48 percent of the five-year cost of owning a vehicle, according to a 2012 analysis from *Consumer Reports*. Fuel is the second biggest expense by a wide margin, accounting for 24 percent of the cost. This indicates that there should be some pressure for drivers to substitute private vehicle usage with other forms of transportation when fuel costs are higher. One factor which would complicate this effect is the presence of electric cars. For example, Hagman et al. (2016) find that fuel costs represent just 3 percent of the total cost of ownership for one electric vehicle model. If the popularity of electric cars increases over time, this could influence the relationship between gas prices and transit usage.

The cost of public transit varies based on the mode of transportation. Per the 2015 FTA report, most forms of rail transportation are more expensive than bus transit on a cost per unlinked passenger trip basis but cheaper than bus transit on a cost per passenger mile basis.

Unlike cars, most of which operate using gasoline, modes of public transit use various energy sources. Many forms of rail, including most light rail, commuter rail, and heavy rail systems, are powered with electricity. For example, the New York City subway uses 1.8 billion kilowatt hours of electric power per year[4]. In turn, New York state[5] receives more than 90 percent of its electricity from a combination of natural gas, nuclear power, and hydroelectric power. Even among transit vehicles that do use traditional fuel sources, diesel fuel is more common than gasoline by a factor of four, according to the same FTA report.

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[4] https://www.nycsubway.org/wiki/Subway_FAQ:_Facts_and_Figures#Power
[5] https://www.eia.gov/state/analysis.php?sid=NY

These factors imply that an increase in gas prices would be unlikely to have much of an impact on the prices paid by public transit riders, removing one potential source of endogeneity in the estimates of the cross-price elasticity.

There are also many factors which affect the relative costs and benefits of switching passengers between private vehicles and public transit. Since public transit requires large subsidies from local, state, and federal governments to operate, expanding public transit networks incurs a public cost. However, this can be offset by benefits of reduced automobile travel including less congestion, less air pollution, and fewer traffic accidents. These benefits, and others, are discussed more thoroughly in Litman (2005)[6], but I do not go deeper into that area in this paper.

2.2 Demographics of public transit users

A 2017 document from the American Public Transit Association[7] provides information about the demographic of public transit riders. According to their surveys, 13 percent of US households have income below $15,000, but 21 percent of transit users do. These figures are 23 percent vs. 21 percent respectively for households with income over $100,000. They also find that the demographics differ between modes of transit. For example, white people tend to ride rail rather than the bus, while the opposite is true for Black and Hispanic people. Also, wealthy people tend to ride rail more than the bus, while the opposite is true for those with lower incomes. Their results indicate that there is significant substitution between driving and riding, as they find that 54 percent of transit riders say they "have a vehicle available on an ongoing basis"

[6] https://www.vtpi.org/tranben.pdf
[7] https://www.apta.com/wp-content/uploads/Resources/resources/reportsandpublications/Documents/APTA-Who-Rides-Public-Transportation-2017.pdf

and that 65 percent of transit users have a driver's license. Another statistic directly relevant for my work is that 7 percent of riders list saving money on gas as their primary reason for riding transit.

2.3 Prior estimates of cross-price elasticity

There are two approaches to estimating the cross-price elasticity of interest. The first involves gathering data on gas prices and transit usage from a single region during a certain period. For example, a researcher might investigate how transit usage in one state responds to a large, presumably exogenous increase in gas prices. The advantage of this approach is that it results in more plausible internal validity since the increase in gas price is determined not to be related to transit usage in that place during that time. The disadvantage of this approach is that the estimates may not satisfy external validity. That is, the estimated effect might only apply to the area and time period specified rather than under more general conditions. The other approach involves estimating the elasticity across regions and time periods. This could be done either by analyzing aggregate data across the country or by using panel data from many areas over many years. The advantage of this approach is that it allows us to be more confident the results are not specific to a particular area, but it can potentially obscure interesting heterogeneity in the effect. In this section, I first describe attempts to identify the elasticity using the first approach and then discuss attempts at the second approach. I also discuss how my analysis contains benefits from both approaches.

Yanmaz-Tuzel and Ozbay (2010) examine the effect of gas prices on New Jersey Transit ridership numbers. They examine large increases in gas prices in 2005 (because of Hurricane Katrina) and 2008 (because of high oil prices). They estimate that the short-term cross-elasticity of transit ridership with respect to gas prices is between 0.12 and 0.22 and the medium-term cross-elasticity (i.e. after several months) is between .028 and .176. The advantage of this study is that we can be relatively confident the estimates are unbiased, since Hurricane Katrina and 2008 oil price rises are plausibly uncorrelated with unobserved factors affecting New Jersey transit ridership supply and demand. While this information is valuable, there are concerns about how much it would generalize to other settings. For example, the demand response for transit could be unique to New Jersey or different for a large, transitory shock due to oil prices than a substantial increase in the fuel tax. Also, since this study only used data from periods in which gas prices increased rapidly, the estimated elasticities may not generalize to periods of more gradual gas price increases or gas price decreases.

Chen, Varley, and Chen (2010) also use New Jersey Transit data on trips via commuter rail into New York City to estimate the effect of an increase in gas prices on transit ridership. Unlike Yanmaz-Tuzel and Ozbay, they use monthly data from between 1996 and 2009 rather than data from brief periods of large gas price increases. They estimate a short-term elasticity of 0.105 and a long-term elasticity of 0.191, and they also find evidence of consumers responding more noticeably to price rises than to price decreases.

A study which uses cross-sectional data instead and is the most similar in structure to mine, is Iseki and Ali (2015), who used several techniques to estimate the effect of fuel price changes on bus, light rail, heavy rail, and commuter rail in 10 cities from 2002-2011. They estimated an overall short run elasticity of 0.06 and found that fuel price increases only had a significant effect in the short run on bus usage, but that they had a significantly positive effect on all the modes in the long run. They also found evidence of non-linear effects, with gasoline price increases seeming to boost transit ridership more when the price was above a threshold of $3.

While their methods look very similar to mine using similar data, they use some different fixed effects and control variables. They also do not consider the impact of fuel taxes or using state gas price as an instrumental variable for local gas prices.

Other papers have investigated the price-elasticity of demand for gasoline itself, that is the change in the quantity demanded of gasoline due to changes in its price. There is substantial disagreement in the literature on this elasticity, with some studies finding gasoline to be quite inelastic and others finding higher elasticities. Hughes, Knittel, and Sperling (2008) use monthly time series data on US gas prices and consumption and find relatively low short-run price elasticities ranging between -.034 and -.077 between 2001 and 2006, down from their estimated short-run price elasticities of -.21 and -.34 between 1975 and 1980. Park and Zhao (2010) find similar results — with relatively elastic demand in the 1970's and inelastic demand in the early 2000's — using aggregate time series data from the United States. However, Levin, Lewis, and Wolak (2016) argue these results underestimate the true elasticity because of excessive aggregation over geographies and time. Using data on daily credit card charges at gas stations in 243 US cities between 2006 and 2009, they estimate short-run elasticities between -.27 and -.35. The existence of a substantial decrease in gasoline usage due to price increases suggests the possibility of public transit usage compensating for decrease in private vehicle travel.

Other research has analyzed the own-price elasticity of transit usage. Dunkerley et al. (2018) perform a broad survey of the literature concerning bus fare elasticity in the UK. They find that the overall long run elasticity is between -0.7 and -0.9, but that it varies between urban and rural areas and between commuting and leisure trips. Comparing these results to estimates of the cross-price elasticity of transit with respect to gas prices, it seems that bus ridership numbers are much more sensitive to changes in fare than to changes in fuel prices. Their work also indicates that consumers making leisure trips may be more price sensitive than those commuting to work.

2.4 Gas taxes vs. gas prices

Most of the prior research on the effect of gas prices on public transit usage has not distinguished between changes in gas price due to ordinary fluctuations and changes due to shifts in tax policy. However, there are both theoretical and empirical reasons to suspect that increases in gas taxes might lead to larger demand response for transit than equally large increases in gas prices for other reasons.

From a behavioral perspective, increases in the gas tax might be more noticeable than typical changes in gas prices due to news coverage of the tax hike. Also, gas tax increases might be considered more likely to be permanent than an ordinary shift, since governments change tax policy less often than gas prices change. This factor could lead to a larger shift in the long-run elasticity of gas price on public transit usage. For instance, the marginal car driver in a large city might continue to commute to work by car despite an temporary increase in gas prices but decide not to buy a new car and rely on transit instead if a seemingly permanent increase in the gas tax was announced.

Donna (2018) builds off this intuition with a structural model of transportation choice. In his model, consumers with heterogenous preferences over modes of transportation choose a mode in each period and "incur a switching cost if the mode chosen in the current period differs from the one in the previous period," which represents "the costs of seeking information and setting up an alternative mode." Thus, consumers are more likely to shift their transportation behavior in response to a permanent gas tax than in response to a transitory gas price increase.

Using transportation data from Chicago, his fitted model predicts that a gas tax would lead to an increase in transportation ridership and that the long-run cross-price elasticity is larger than the short-run price elasticity.

Adjacent empirical work also supports this argument. For instance, Li, Linn, and Muehlegger (2014) look at gas tax and consumer behavior data between 1966 and 2008 and find that gas taxes are more likely than gas price increases to decrease gasoline consumption and vehicle miles travelled and increase consumption of fuel-efficient vehicles.

One paper which considers the effect of fuel taxes on transit usage directly is Storchmann (2001), which differentiates between types of trip using German transit data from 1980 to 1995 and finds a cross-price elasticity of transit usage ranging from 0.202 for work trips to 0.045 for leisure and 0.031 for shopping trips. One conclusion of this research is that fuel taxes may increase transit demand during peak hours (when people are commuting to work) more than demand during off-peak hours. However, this study seems to estimate the effect of a hypothetical fuel tax with a structural model of transit demand and costs rather than actual data on fuel taxes. Even if these approaches are equivalent, this study differs from my work since it examines a different country during a different time period, so the results are unlikely to be directly transferable.

Gimenez-Nadal and Molina (2019) look at how gasoline tax rates affect commuter behavior and find that higher gasoline tax rates lead to less commuting by car and more commuting by public transit and biking/walking. Their paper provides key evidence that gasoline taxes can cause people to substitute driving with public transportation. The difference with my work is that this paper only looks at commuting trips rather than all trips. I also differentiate between modes of public transportation

2.5 Optimal gas tax literature

My work also relates to the extensive literature on optimal fuel taxation. One common issue in this literature is that consumers can respond to fuel taxes by purchasing more fuel-efficient cars but not reduce their driving. This may correct somewhat for carbon emissions externalities but fail to correct other externalities, like congestion and traffic accidents. As Parry and Small (2005) write, "It is crucial to account for the endogeneity of fuel economy: to the extent that people respond to higher fuel taxes by purchasing more fuel-efficient vehicles rather than driving them less, the contribution of distance-based externalities to the optimal fuel tax is substantially diminished." The substitution of driving for transportation in response to gas taxes or gas price increases can complicate this phenomenon. If some consumers respond to taxes by using public transit as their primary mode of transportation, gas taxes might be more effective than expected in diminishing externalities due to traffic congestion and air pollution.

Other strands of the literature investigate the relationship between gas usage and "leisure consumption". To the extent leisure is overconsumed because it is not taxed, decreasing the consumption of leisure can make gas taxes (or any excise tax) more efficient. West and Williams (2007) find that "gasoline is a leisure complement … Even if gasoline usage entailed no negative externalities at all, the optimal gas tax would still almost equal the average rate in our sample." If transit usage is a relevant substitute for gasoline usage, understanding how transit usage relates to leisure consumption would become relevant for estimating this component of the optimal gas tax (though my paper does not try to calculate this relationship).

2.6 Effect of Uber on public transportation

Finally, my work relates to the branch of literature which investigates the effects of the introduction of Uber on transportation networks and private automobile usage. Hall, Palsson, and Price (2018) investigate whether Uber is a complement or substitute to public transportation. On one hand, Uber could decrease public transportation ridership by causing people to use the service rather than take public transit. On the other hand, Uber could increase public transit by allowing riders to take Uber to complete trips involving public transportation, helping to overcome the inconvenience of the fixed-route, fixed-time nature of public transit. Using data from 196 Metropolitan Statistical Areas (MSAs), they find that Uber is on average a complement to public transit, but there is significant variation by area.

Gong et al. (2018) find that Uber entry was correlated with an 8% increase in vehicle ownership, which they hypothesize is due to the ability to earn money as a vehicle owner by driving for Uber.

Since these papers provide evidence that Uber has changed transportation habits, my paper investigates whether Uber entry has affected my elasticity of interest.

3. Data

3.1 Data Sources

For my regressions with city-level data, I used monthly data on gas prices, public transportation usage, and demographic statistics between 2006 and 2018 for ten major cities in the United States.

I pulled my data from three main sources. For information on gas prices, I used the U.S. Energy Information Administration database. The US EIA releases information at the weekly, monthly, and annual level for gas prices in ten cities: Boston, Chicago, Cleveland, Denver, Houston, Los Angeles, Miami, New York City, San Francisco, and Seattle. These are the ten cities I used for my analysis. The gas prices released by the US EIA include all grades and formulations of gas and are estimated at the local level by collecting gas prices for regular gasoline and diesel at certain locations and extrapolating based on other surveys and demographic data from the US Census Bureau. The data exists for some cities between 2000 and 2019 and for all cities between 2003 and 2019. I only use data from January 2006 to December 2018 since this is the time span for which geographic demographic variables are available from the ACS.

For most states, the US EIA provides average gas prices only on an annual basis, but for nine states, they provide data on a monthly basis: California, Colorado, Florida, Massachusetts, Minnesota, New York, Ohio, Texas, and Washington. These prices are estimated the same way as the city-level price data. The amount of aggregation involved in calculating the transit usage for an entire state may make this data less useful for calculating the overall elasticity of transit usage and gas prices. However, I use this data in one specification for more precisely determining the impact of a state's increase in gas taxes.

These price series are reported in terms of nominal rather than real prices, but in most cases I choose not to adjust for inflation. I made this decision for three reasons. First, inflation was relatively low between 2006 and 2018, so adjusting for inflation should not have a major impact. Second, gas prices may be affected by inflation earlier than transit fares, which tend to be rigid. This means, as a hypothetical example, a 1% increase in gas prices due to inflation would not be considered an increase in the real price of gas, but it could still affect the relative cost of transit and private vehicle usage for the consumer in the short and medium run. Third, adjusting for inflation could cause complications when considering gas taxes, which often remain constant from year to year. Using inflation-adjusted rates would result in these taxes appearing in the data as steadily decreasing, which is likely not a desirable property for this analysis since consumers would probably react differently to intentional increases in gas taxes than to gas taxes that change only in real terms. Nonetheless, I perform one version of my analysis with inflation-adjusted gas prices to see how this affects results and confirm in Appendix B.2 that this decision does not have a major impact.

For information on public transportation usage, I used the National Transit Database (NTD) published by the United States Department of Transportation. The NTD reports transit statistics for 850 urbanized areas (UZA), which occasionally but infrequently cross state lines. The only statistic available at the monthly level was the number of Unlinked Passenger Trips (UPT), which measures the number of times passengers board a public transportation vehicle. That means, for instance, a person who takes a bus followed by light rail to get to work would count for two UPT per trip. The NTD offers separate numbers for various modes of transportation (e.g. bus, light rail, and heavy rail) for each area. For some analyses I looked only at data for total trips, and for others I distinguished trips by mode of transportation. The NTD tracks modes of transportation as intriguing as Aerial Tramways and Cable Cars, but the most salient modes for all cities are bus and rail services. In terms of rail, the NTD distinguishes between Light Rail ("an electric railway which intersects vehicular traffic at grade crossing and is typically powered by overhead wires"), Heavy Rail ("an electric railway that operates on exclusive track with the ability to carry a heavy volume of passengers"), and Commuter Rail ("a railway for urban passenger travel on the general railroad system between a central city and adjacent suburbs"). In terms of bus travel, the NTD distinguishes between Bus Rapid Transit, Commuter Bus, Bus, and Trolleybus. For most of my analysis, I break up the categories into Light Rail, Heavy Rail, Commuter Rail, and Bus travel for the sake of uniformity, though this does omit a small number of trips on less common services.

The NTD data is available between 2002 and 2019, but again I only use data from January 2006 to December 2018. I do not believe that missing data plays a major role for any of the cities during this time period, though not every city offers every mode of transportation.

The US Department of Transportation's Federal Highway Administration provides fuel tax rates for every state. The figures in this data set refer only to the per-gallon excise tax levied on gasoline. The federal excise tax on gasoline, which has not changed since 1993, is 18 cents per gallon, but this is not included in the data. Most states tax gasoline using per-gallon excise taxes, although some also have sales taxes which apply to gasoline. The FHA reports each of the states' excise tax on an annual basis but does not include any sales taxes. This can lead to some confusions in the data, like an apparent massive tax increase in California in 2010, which was actually caused by California, for arcane budgetary reasons, raising its excise tax on gasoline while offsetting the expense to consumers with a decrease in the sales tax applied to gasoline. Appendix A.3 shows the fuel tax rate for each state from 2006 to 2018.

For demographic data to be used in my regressions as control variables, I collected data from the 1-year American Community Surveys (ACS) published by the Census Bureau. The ACS samples 1.7% of households, which means its estimates at the local level are not exact, but I would expect them to be accurate enough for the large cities in my study. For each city, I used data on the population density, real median household income, unemployment rate, proportion of children under 18, proportion of adults over 55, proportion of foreign-born residents, proportion of households with no vehicles, and average commute to work (in minutes). The ACS is available between 2006 and 2018.

Finally, for information on the timing of Uber entry into these cities, I used the database compiled by Hall et al. (2018) from Uber press releases and other news sources. They provide information on UberX and UberBlack entry, but I use the dates of UberX entry since this service is more popular. Their records indicate that Uber entered most of the cities between 2012 and 2014. The earliest recorded entry into one of my cities is San Francisco in 2010 and the latest is Miami in June 2014.

Each of these data sets distinguishes between geographic areas in a slightly different way. For example, the gas price data seems to refer to an area for each city that is less expansive than the urbanized areas for which data is reported in the NTD. I do not anticipate this being a major factor for my analysis since gas prices likely do not vary too much within a metropolitan area.

3.2 Summary Statistics

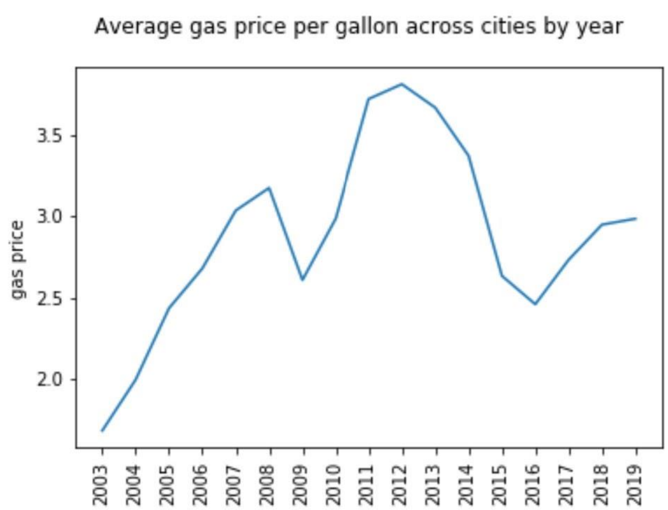
In this section, I offer summary statistics and charts to help understand the gas price and transit data.

In the table below, I provide basic descriptive statistics about each of the main variables used in my regressions, including the log of unlinked passenger trips and the log of gas price. Between the 10 cities and 12 years in my data, there is a total of 1,560 observations.

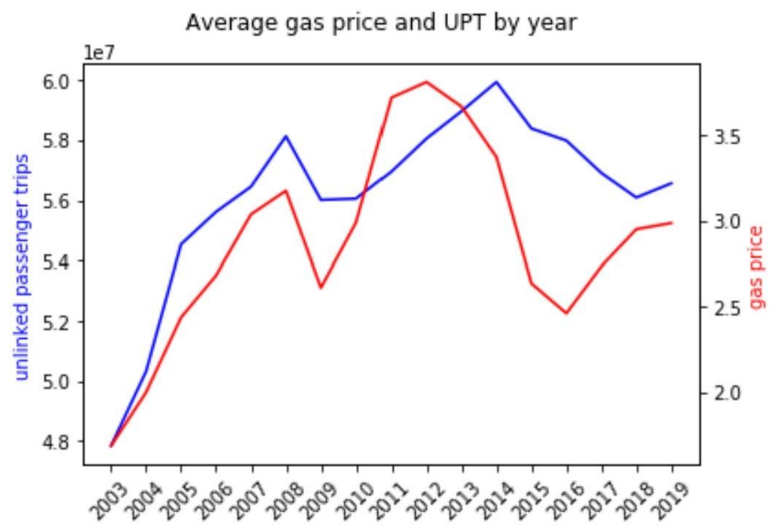
Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Population under 18	1560	.2	.04	.13	.27
Unemployment Rate	1560	.09	.04	.03	.21
Median HH Income	1560	51587.37	17399.88	24257	112376
Average Commute	1560	29.47	4.72	23	42
No Vehicle HH	1560	.24	.13	.08	.56
Foreign-born Pop	1560	.28	.14	.04	.59
Population over 55	1560	.23	.03	.18	.29
log(UPT)	1560	16.99	1.22	14.81	19.8
log(Gas Price)	1560	1.1	.21	.46	1.51
Population Density	1560	7244.26	4298.58	3208.18	18405.69

The graph below shows the annual average gas price averaged across the 10 cities using the EIA data. The graph indicates that there is significant variation over time, with gas prices ranging from under 2 dollars per gallon in 2003 to nearly 4 dollars a gallon in 2012. Note that these numbers are in nominal terms.

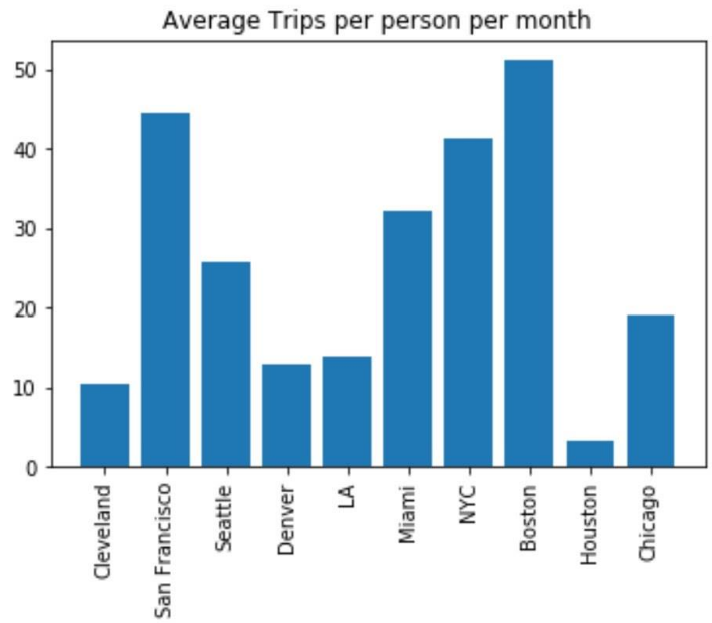


In the next graph, I superimpose a plot of annual UPT averaged across the 10 cities with average gas price for those cities using NTD and EIA data. This graph suggests there is significant correlation between the two measures. One interesting pattern is the number of UPT peaking at the same time or shortly after a peak in gas prices, which could be consistent with people switching their transportation habits from driving to using transit in response to high gas prices.



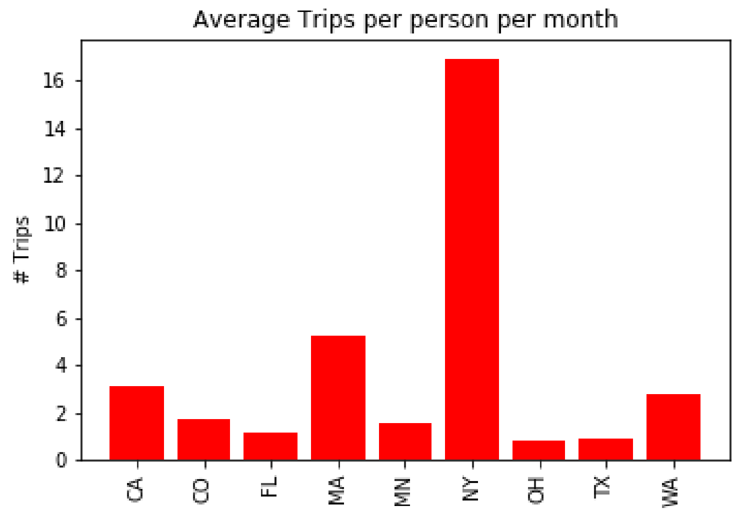
In Appendix A.1 I plot the monthly average gas price and UPT count separately for each city. These plots show us that there appears to be significant seasonal variation for both the gas price and UPT count. In many cities, the curves appear to track relatively closely to one another, though there are some instances (like in Cleveland and Houston) where the two diverge dramatically for a period. These charts also indicate that gas prices and transit usage vary both within cities and between cities over time.

Cities have different transportation network coverage and breakdowns between modes of transit. The chart below, based off NTD and ACS data, shows the average number of UPT per month, normalized by the number of people in each city. It indicates that Boston, San Francisco, and New York have the most developed transit networks, while Cleveland, Houston, Denver, and Los Angeles have the least developed.



In Appendix A.2 I break down each city's transit network by proportion of riders in each mode using pie charts. These charts indicate that the cities with more developed transit networks (like Boston and New York) rely more heavily on rail systems, while cities with less developed transit networks (like Houston and Cleveland) rely more heavily on bus systems.

Finally, the chart below, also with NTD and ACS data, shows the average number of passenger trips per month for each of the nine states with monthly transit and gas data available. New York has by far the largest number of passenger trips per month, and Minnesota, which I later rely on to estimate the effect of a fuel tax, has a middle-of-the-road transit system.



4. Methodology

4.1 Baseline regression with city-level data

The first set of specifications aim to estimate the effect of gas prices on public transportation usage with panel data from the 10 cities. The main specification in this category involves fixed effects for city, month, and year to control for local, seasonal, and long-term time trends respectively. That is, I estimate:

$$\log q_{it} = \alpha_0 + \alpha_1 \log p_{it} + \gamma_i + \delta_t + \beta X_{it} + \varepsilon_{it}$$

where q_{it} is the number of UPT in city *i*, time *t*, α_0 is the intercept parameter, p_{it} is the gas price in city *i*, time *t*, γ_i is a city fixed effect, δ_t is a month fixed effect, and X_{it} is the vector of demographic controls collected from the ACS. These variables include the population density of the area, the proportion of the population under 18, the proportion of the population over 65, the unemployment rate, the median household income, the length of an average commute to work, the proportion of vehicles which don't own a vehicle, and the proportion of the population born outside of the United States. α_1 is the coefficient of interest. Because of the log-linear structure of the regression, it represents the cross-price elasticity of transit ridership with respect to gas prices.

The city fixed effects account for unobserved factors for each city which lead to different levels of transportation ridership. The month fixed effects account for seasonal variation in transit ridership demand. Unlike some prior papers, I do not include year fixed effects in my baseline specification. The reason for this decision is that year fixed effects would prevent the identification of a nationwide change in transit ridership in a particular year due to a change in gas prices in that year. For example, the plot of both monthly average gas price and transit ridership over time which I presented in the Data section shows that gas prices and transit ridership seemed to peak simultaneously in some years. Since the regression includes city and month fixed effects, the elasticity is identified by within-city variation, adjusted for seasonal effects.

4.2 Baseline regression with mode of transit

I also consider an identical model as the above, except with trips broken up into Heavy Rail, Light Rail, Commuter Rail, and Bus trips. In each of these regressions, the q_{it} on the left side of the equation refers only to the number of trips for one mode of transit in city *i* at time *t*. These regressions can provide evidence whether the effect differs between modes of transit. Since cities vary in the composition of their transit networks, such a difference would imply that changes in gas prices could affect some areas and demographics more than others.

4.3 Baseline regression with state gas price IV

Even with fixed effects and control variables in the regression, we might still be concerned about idiosyncratic shocks at the city level that affect both gas prices and public transportation usage in the same direction. For instance, there could be one-time events that bring many people into a city in one month, leading to a higher demand for gas and public transportation. Thus, I also consider an instrumental variables approach, using the average gas price in the state containing a city as the instrument. The idea is that the state gas prices are correlated with city gas prices but are less prone to city-specific shocks. Monthly gas data was available for all the necessary states, except for Illinois, so I used Minnesota gas data as an instrument for Chicago gas data instead.

The IV regressions look the same as the regressions above, except with the state gas instead of the city gas for $\log p_{it}$. I also confirm that state gas price is a strong enough instrument for local gas price with the first-stage regression below. With an F-statistic over 3,000, the first-stage regression indicates that state gas price is a sufficiently strong instrument.

Table 4.3

VARIABLES	(1) Log(State Gas)
Log(City Gas)	0.826***
	(0.0144)
Constant	0.178***
	(0.0161)
Observations	1,560
R-squared	0.680

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

4.4 Baseline regression with lags

To determine whether the medium- or long-term elasticity differs from the short-term elasticity, I consider regressions of transit ridership in a period on gas prices six and twelve months before. My main lagged specification can be written as

$$\log \mathrm{q_{it}} = \alpha_0 + \alpha_1 \log \mathrm{p_{it}} + \alpha_2 \log \mathrm{p_{it-6}} + \alpha_3 \log \mathrm{p_{it-12}} + \gamma_\mathrm{i} + \delta_\mathrm{t} + \beta \mathrm{X_{it}} + \varepsilon_\mathrm{it}$$

Where each variable is defined as before and p_{it-6} and p_{it-12} represent the 6-month lag and 12-month lag of gas prices. I include city and month fixed effects but not year fixed effects since controlling for the baseline in a year seems like it would artificially underestimate the true effect if gas prices rising nationwide in the previous year did in fact lead to an increase in transit usage.

4.5 Baseline regression with mode of transit and lags

As with the original model, I also consider specifications of the lagged model with trips broken up by mode of transportation. Again, these regressions are the same as above, except with q_{it} referring only to monthly trips for one mode of transit. These regressions allow us to see whether the medium- and long-term effects of gas price changes differ between modes of transit.

4.6 Uber entry effects

The next specification aims to estimate how the introduction of Uber to cities affected this relationship between gas prices and public transportation. To do this, I estimate separate coefficients on the gas price parameter based on whether Uber has entered the city. The main specification of that form looks as follows:

$$\log q_{it} = \alpha_0 + \alpha_1^{pre} \log p_{it} \, \Pi(pre) + \alpha_1^{post} log p_{it} \Pi(post) + \gamma_i + \delta_t + \rho_y + \beta X_{it} + \varepsilon_{it}$$

Where the variables are the same for above, except for the indicator functions $\Pi(pre)$, which takes on the value 0 if Uber exists in city *i* at time *t* and 1 otherwise, and $\Pi(post)$, which equals 1 if Uber exists in city i at time t, and 0 otherwise. I am interested in the difference between the coefficients α_1^{pre} and α_1^{post}, which represents the difference in the effect of gas prices in public transportation usage after Uber enters a city. For the main specification of this form, I only consider data from 2010 to 2014, so the difference in coefficients is identified by the difference in the elasticity in areas where Uber had yet to enter and where Uber had already entered, adjusted for the national trend.

4.7 State gas tax panel data regression

With my next set of regressions, I attempt to quantify the cross-price elasticity of transit usage with respect to gas taxes and see how it differs from the cross-price elasticity with respect to gas prices. Both gas taxes and gas prices for all 50 states are reported only on an annual basis, so I use annual, rather than monthly, data for these regressions. For the first regression of this type, I adapt the framework used by Li, Linn, and Muehlegger to simultaneously estimate the price elasticity of gas with respect to its own price and fuel taxes.

$$\log q_{it} = \alpha_0 + \alpha_1 \log p_{it} + \alpha_2 \log\left(1 + \frac{\tau_{it}}{p_{it}}\right) + \gamma_i + \delta_t + \beta X_{it} + \varepsilon_{it}$$

These variables are defined as before, except q_{it} is the yearly number of UPT, p_{it} is the tax-exclusive price of gasoline in the state averaged over a year, and τ_{it} is the gas tax for state *i* in year *t*. Under this framework, the cross-price elasticity with respect to gas prices (ε_p) and with respect to gas taxes (ε_τ) are:

$$\varepsilon_p = \alpha_1 - \alpha_2 \frac{\tau}{p + \tau}, \qquad \varepsilon_\tau = \alpha_2 \frac{\tau}{p + \tau}$$

I also consider a simpler regression of transit usage on gas prices and gas taxes, albeit without the simple conversion from coefficients to cross-price elasticities:

$$log\, q_{it} = \alpha_0 + \alpha_1\, log\, p_{it} + \alpha_2\, log\, \tau_{it} + \gamma_i + \delta_t + \beta X_{it} + \varepsilon_{it}$$

4.8 Minnesota difference-in-differences

One issue with determining whether gas taxes are associated with higher rates of transit usage is that there are few examples of large increases in gas taxes. The federal gas tax has not been raised since 1993 (which was before the NTD began collecting data on transit usage), and there are few instances of states making large increases in gas taxes. Li, Linn, and Muehlegger were able to identify the effect of gas taxes on gas usage and car purchases using 50 years' worth of data, which is not an option for identifying the effect on transit usage due to data unavailability. The fact that gas tax changes happen on an annual, rather than monthly basis, make identification even more difficult.

An instance of a large state gas tax increase can be seen in Minnesota in 2008. In 2008, the Minnesota state government[8] passed legislation to gradually raise the fuel tax from 2008 to 2012. Between April and October 2008, Minnesota authorized three separate increases in the state gas tax, raising the tax per gallon from 20 cents to 25.5 cents. The tax continued to increase gradually until 2012, when it reached 28.5 cents per gallon. Like most states, Minnesota does not apply a sales tax to fuels subject to an excise tax, including gasoline, diesel, and gasohol.

This significant increase in the gas tax allows us to set up a rudimentary difference-in-differences specification to determine if there was a resulting increase in transit usage. The

[8] http://www.dot.state.mn.us/about/pdfs/historychart.pdf

difference-in-difference mechanism is a popular way to estimate the effect of a policy enacted somewhere but not everywhere at the same time. In this case, we can use the states which did not raise their gas taxes substantially during the time period of interest to estimate the effect of Minnesota raising its gas tax in 2008. Fortunately for this paper, Minnesota is one of the nine states for which the EIA publishes monthly gas prices, and none of the other states raised their gas taxes between 2006 and 2013, except for New York, which has a slightly fluctuating gas tax from year to year. This allows me to identify the effect in the month the gas tax was finalized, October 2008, using the following regression framework:

$$log\, q_{it} = \alpha_0 + log\, p_{it} + \alpha_1 \mathrm{POST}_t + \alpha_2 \mathrm{POST{*}TREAT}_{it} + \gamma_i + \delta_t + \rho_y + \beta X_{it} + \varepsilon_{it}$$

In this model, q_{it} represents monthly total trips between 2006 and 2013 and p_{it} represents the average gas price for a state. POST_t is a binary variable which takes value one if and only if the observation is from October 2008 or later. $\mathrm{POST{*}TREAT}_{it}$ is a binary variable which takes value one if and only if the observation is from Minnesota and October 2008 or later. γ_i is a state fixed effect, δ_t is a month fixed effect, and ρ_y is a year fixed effect. The coefficient of interest is α_2, the coefficient on the interaction term. Identification comes from the change in Minnesota transit usage after October 2008 compared to the trend in the other states, adjusted for time trends and seasonal effects.

There are several assumptions required to ensure the difference-in-difference estimator is valid. One assumption would be violated if Minnesota enacted its gas tax out of concern transit usage was too low since we might then expect transit usage to increase due to other policies. This appears to not be the case, with road and highway funding as the main reason for the tax increase. The state government allocated just $2.45 million out of the projected $284 million raised by the tax in the 2008 and 2009 fiscal years to "rail, transit, and other port developments." Most of the other funding went to road and highway maintenance, and better maintained roads could plausibly encourage some people to substitute driving for transit even less. The second key assumption is the "Parallel Trends" hypothesis, meaning that transit usage in Minnesota would have to be moving in parallel with usage in other states before the enactment of the tax. This assumption will be discussed in the Results section, though it appears to be approximately correct.

5. Results

5.1 Baseline regression

Table 5.1 shows the result of my baseline regression, of the (natural) log of unlinked passenger trips on the log of the monthly average gas price, city and month fixed effects, and demographic controls. The coefficient of interest, which represents the cross-price elasticity of transit ridership with respect to gas prices because of the log-linear structure of the model, is 0.0252, with a 95 percent confidence interval ranging from just above 0 to 0.0376. This means that a 10 percent increase in the gas price would be expected to lead to a .25% increase in public transit ridership. For the control variables, the unemployment rate is negatively correlated with public transit ridership, while median household income, the length of the average commute to work, and the proportion of households without a vehicle are positively correlated with monthly transit ridership.

Table 5.1

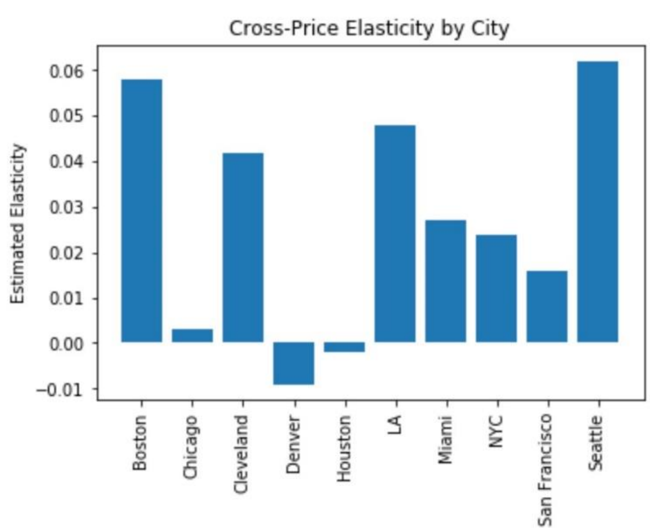
VARIABLES	(1) log(UPT)
log(Gas Price)	0.0252**
	(0.0124)
Population Density	-5.01e-06
	(9.75e-06)
Population under 18	0.490
	(0.374)
Population over 55	-4.045***
	(0.384)
Unemployment Rate	-0.306**
	(0.137)
Median Household Income	2.74e-06***
	(4.61e-07)
Average Commute to Work (in Min)	0.0126***
	(0.00286)
No Vehicle HH	1.436***
	(0.256)
Foreign-born Population	-0.459*
	(0.249)
Constant	17.10***
	(0.177)
Observations	1,560
R-squared	0.996

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

In Appendix B.1, I show the results of this baseline regression with various combinations of city, month, and year effects. This experiment suggests that the results of the regressions are sensitive to the fixed effects used. The estimated elasticity with no fixed effects is 0.433 while the elasticity with no fixed effects is -.0244. The elasticity is 0.287 with month and year fixed effects, -.0024 with city and year fixed effects, and 0.0314 with just city fixed effects. As discussed in the Methodology section, the preferred specification is one with city and month fixed effects.

My results also indicate that the elasticity differs between cities with different levels of transit coverage. In Appendix B.3 are the results of my baseline regression, except run separately for observations from one of the cities with more developed transit networks as defined by ridership per capita (Boston, New York City, Seattle, and Miami) and cities with less developed transit networks (Chicago, Cleveland, Denver, Houston, Los Angeles, and San Francisco). With this regression, I found that the elasticity estimated using the cities in the former category was .0486 while the elasticity estimated using the cities in the latter category was .0281. The result that more people shift their transportation from cars to public transit due to gas price increases in places where transit is better developed is not surprising, but it is important to keep in mind this difference, especially for policy makers considering the effects of a gas price change in a single location.

I also estimated the elasticity with regressions using only data from one city for each city. These results are shown below. For some cities, the elasticity is above 0.05 and for others it is slightly negative. The point of this chart, however, is less about the estimated elasticity for any particular city and, again, more about how there seems to be significant heterogeneity in the effect of gas prices on city-level transportation ridership.



5.2 Baseline regression with mode of transit

Table 5.2 shows the results of the baseline regression differentiated by mode of transit, which is the same as the regression in Table 5.1 except the log of unlinked passenger trips variable on the left side of the regression is split into the log of unlinked passenger trips for a single mode of transit. These estimates show that the cross-price elasticity of light rail ridership with respect to gas prices is the highest at 0.207. The cross-price elasticity of bus ridership is the lowest at 0.010, while the cross-price elasticities for commuter rail and bus ridership are in between at 0.0642 and 0.0548. These results are somewhat surprising considering the demographics of the modes of transit. As discussed in prior sections, rail systems tend to have wealthier customers than buses. Thus, we would expect that bus riders may be more price sensitive and more likely than rail riders to change their transportation habits in response to a change in gas prices, but this appears not to be the case.

Table 5.2

VARIABLES	(1) Light Rail	(2) Heavy Rail	(3) Commuter Rail	(4) Bus
log(Gas Price)	0.207***	0.0548***	0.0642***	0.0103
	(0.0613)	(0.0179)	(0.0203)	(0.0137)
Population Density	0.000939***	6.50e-05***	0.000108***	-2.67e-06
	(6.69e-05)	(1.31e-05)	(1.45e-05)	(1.08e-05)
Population under 18	20.81***	-2.185***	0.683	4.994***
	(1.909)	(0.631)	(0.700)	(0.415)
Population over 55	10.14***	-1.648***	-3.043***	-1.980***
	(1.860)	(0.618)	(0.730)	(0.426)
Unemployment Rate	4.614***	-1.173***	-0.224	0.623***
	(0.705)	(0.204)	(0.247)	(0.152)
mhinc	7.46e-06***	9.46e-07	6.92e-06***	-1.12e-06**
	(2.35e-06)	(6.35e-07)	(6.94e-07)	(5.12e-07)
avg_commute	0.0236	0.00752*	0.0345***	0.0218***
	(0.0149)	(0.00395)	(0.00519)	(0.00317)
No Vehicle HH	6.886***	2.688***	4.147***	1.802***
	(1.300)	(0.393)	(0.429)	(0.284)
Foreign-born Population	1.432	-0.165	-4.437***	0.334
	(1.223)	(0.366)	(0.400)	(0.276)
Constant	-1.327	15.47***	12.89***	14.27***
	(0.870)	(0.336)	(0.355)	(0.196)
Observations	1,248	1,092	1,092	1,560
R-squared	0.908	0.997	0.995	0.995

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

5.3 Baseline regression with state gas price IV

Table 5.3 shows the results of the instrumental variables regression instrumenting a city's monthly average gas prices with state gas prices. These results are directionally similar to the baseline regression but result in a larger estimate of the cross-price elasticity of transit ridership with respect to gas prices, with a coefficient of 0.0548 compared to 0.025. In Appendix B.4, I provide IV estimates of the elasticities for the four disaggregated modes of transit. In this specification, light rail still has the highest cross-price elasticity and Bus still has the lowest, but the magnitudes of the estimates are larger. These IV results are interesting to consider, but since I do not think there should be too many concerns about endogeneity which the IV fixes, I still consider the estimates with local gas prices more important.

Table 5.3

VARIABLES	(1) log(UPT)
Log(State Gas Price)	0.0548***
	(0.0122)
Population Density	-3.63e-06
	(9.70e-06)
Population under 18	0.622*
	(0.372)
Population over 55	-3.956***
	(0.382)
Unemployment Rate	-0.297**
	(0.136)
Median Household Income	2.87e-06***
	(4.60e-07)
Average Commute to Work (in Min)	0.0125***
	(0.00285)
No Vehicle HH	1.227***
	(0.257)
Foreign-born Population	-0.392
	(0.248)
Constant	17.07***
	(0.176)
Observations	1,560
R-squared	0.996

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

5.4 Baseline regression with lags

Table 5.4 shows the results of the regression of log transit ridership on six-month and twelve-month lags of gas price. The coefficients on these variables are 0.0371 and 0.0642 respectively.

These results indicate that the medium to long term impact of gas prices on transit ridership are likely larger than the short-term impact. One explanation for this is that an increase in gas prices may influence some households to choose public transit over new vehicle purchases when making medium and long-term decisions about their transportation needs. They also indicate that studies that only consider the short-term impact of gas prices on transportation usage are likely underestimating the overall effect.

Table 5.4

VARIABLES	(1) Log(UPT)
log(Gas Price)	-0.0180
	(0.0127)
log(Gas Price 6 mo. lag)	0.0371***
	(0.0135)
log(Gas Price 12 mo. lag)	0.0642***
	(0.0122)
Population Density	-3.23e-05***
	(9.22e-06)
Population under 18	0.0486
	(0.370)
Population over 55	-4.042***
	(0.368)
Unemployment Rate	-0.323**
	(0.127)
Median HH Inc	2.92e-06***
	(4.34e-07)
Avg Commute	0.0123***
	(0.00265)
No Vehicle HH	1.369***
	(0.244)
Foreign-born Population	0.171
	(0.236)
Constant	17.16***
	(0.168)
Observations	1,440
R-squared	0.997

Standard errors in parentheses

5.5 Baseline regression with mode of transit and lags

Table 5.5 shows the results of the regressions identical to the previous one except with transit ridership disaggregated by mode of transit. Among the coefficients on the six-month lag of gas prices, heavy rail, commuter rail, and bus are all positive at a statistically significant level. Interestingly, the same is true only for heavy rail and bus for the twelve-month lag of gas prices. These results suggest that bus ridership is more elastic with respect to gas prices in the medium- and long-term and could be explained by less wealthy heavy rail and bus riders being less likely to purchase a new vehicle when gas prices rise.

Table 5.5

VARIABLES	(1) Light Rail	(2) Heavy Rail	(3) Commuter Rail	(4) Bus
log(Gas Price)	0.133**	-0.0227	-0.0174	-0.0295**
	(0.0643)	(0.0190)	(0.0205)	(0.0143)
log(Gas Price 6 mo. Lag)	0.0938	0.0820***	0.101***	0.0319**
	(0.0686)	(0.0200)	(0.0218)	(0.0153)
log(Gas Price 12 mo. Lag)	-0.108*	0.124***	0.0258	0.0662***
	(0.0618)	(0.0186)	(0.0202)	(0.0139)
Population Density	0.000879***	4.72e-05***	7.85e-05***	-4.33e-05***
	(6.89e-05)	(1.29e-05)	(1.34e-05)	(1.04e-05)
Population under 18	14.62***	-2.653***	1.838***	4.612***
	(1.915)	(0.679)	(0.710)	(0.419)
Population over 55	5.644***	-2.151***	-1.925***	-2.011***
	(1.820)	(0.641)	(0.712)	(0.417)
Unemployment Rate	4.421***	-1.468***	-0.0910	0.495***
	(0.678)	(0.200)	(0.230)	(0.144)
Observations	1,152	1,008	1,008	1,440
R-squared	0.920	0.998	0.996	0.996

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

5.6 Entry of Uber

Table 5.6 shows the results of my regression investigating the effect of Uber entry on the cross-price elasticity of transit usage with respect to gas prices. The similarity of the coefficients on the two interaction terms of the binary variable representing Uber entry and gas price (Pre-Uber and Post-Uber) indicates that this regression does not provide evidence of such an effect. Since I only use data from 2010 to 2014 (the earliest and latest year in which Uber entered one of the cities in my data set), identification relies on the difference in elasticities between places where Uber had been introduced and where Uber had not yet been introduced. However, these results cannot rule out the possibility that Uber introduction and growing popularity contributed to an increase in the cross-price elasticity after it had been introduced to all ten cities. In Appendix B.5, I include results from a similar regression to the one below, except all years are included and no year fixed effects are used. In this specification, the coefficient on the interaction term between Uber entry and gas price is positive at a significant level. However, it is difficult to determine from this evidence alone whether Uber entry and development is responsible for this change in later years in the data.

Table 5.6

VARIABLES	(1) log(UPT)
Pre-Uber	0.0275
	(0.0186)
Post-Uber	0.0180
	(0.0186)
Population Density	6.50e-05**
	(2.61e-05)
Population under 18	1.666***
	(0.594)
Population over 55	-1.758***
	(0.678)
Unemployment Rate	0.185
	(0.233)
Median Household Income	1.39e-06
	(1.03e-06)
Average Commute to Work (in Min)	0.00820**
	(0.00340)
No Vehicle HH	0.917***
	(0.273)
Foreign-born Population	0.710**
	(0.289)
Constant	15.96***
	(0.371)
Observations	600
R-squared	0.999

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

5.7 State gas tax panel data regression

Table 5.7 shows the results of the 50-state regression of annual transit ridership on the gas tax and the gas price. The left column shows the regression of transit ridership on gas price and the ratio of the gas tax to the gas price, and the right column shows the regression of transit ridership on gas price and the raw gas tax. Unexpectedly, the coefficients on the tax variables — Tax

Ratio and log(Gas Tax) — are negative, though the confidence intervals are extremely wide. There are a few reasons this could have happened. First, the fact that the data was available on only an annual basis may have resulted in too much aggregation to accurately identify any effect. Second, many states did not change their gas tax at all during the time period, and even among the ones that did, the change was typically quite small. Thus, there may not be sufficient variation in a large enough sample size to identify the true effect.

Table 5.7

VARIABLES	(1) 'Tax Ratio'	(2) 'State Gas Tax'
log(Gas Price)	0.140***	0.151***
	(0.0500)	(0.0292)
Tax Ratio	-0.188	
	(0.533)	
Total Population	3.93e-09	4.51e-09
	(1.89e-08)	(1.89e-08)
Population under 18	1.649	1.621
	(1.847)	(1.846)
Population over 55	0.503	0.505
	(0.719)	(0.718)
Unemployment Rate	1.476***	1.469***
	(0.360)	(0.360)
Median Household Income	5.54e-06**	5.45e-06**
	(2.56e-06)	(2.56e-06)
Average Commute to Work (in Min)	0.00938	0.00979
	(0.0119)	(0.0119)
Foreign-born Population	-2.497*	-2.459*
	(1.457)	(1.456)
log(Gas Tax)		-0.0249
		(0.0333)
Constant	15.53***	15.46***
	(0.644)	(0.651)
Observations	618	618
R-squared	0.996	0.996

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

5.8 Minnesota difference-in-differences regression

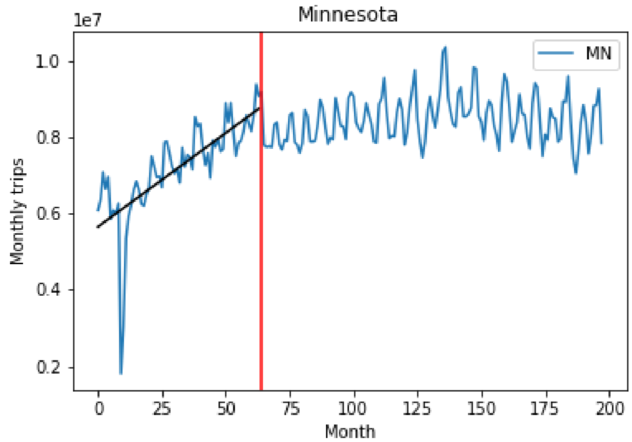
Table 5.8 shows the results of the difference-in-differences regression using Minnesota's state gas tax increase in 2008 as a natural experiment. These results indicate that the tax increase had a significant impact on public transit ridership, as the coefficient of interest — POST_TREAT — is statistically significant even when controlling for the actual gas price. This outcome may differ from the one in the previous regression since monthly data was available for Minnesota to more accurately measure the change in transit ridership to the timing of the tax increase. The difference-in-difference specification also allows for the measurement of longer-term effects of the tax on transit ridership, which may be important in the case of a permanent tax increase. However, it is difficult to know from one such study how these results would generalize to other locations.

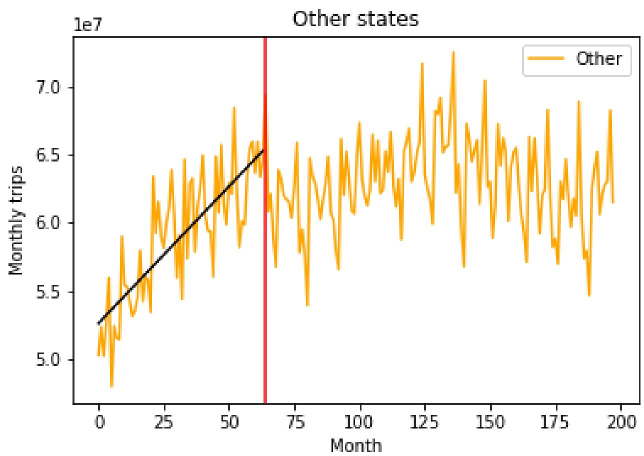
Table 5.8

VARIABLES	(1) log(UPT)
log(Gas Price)	0.0302
	(0.0257)
POST	-0.0208
	(0.0182)
POST_TREAT	0.0759***
	(0.0149)
Total Population	-1.57e-08*
	(8.30e-09)
Population under 18	3.444**
	(1.522)
Population over 55	-5.071***
	(1.677)
Unemployment Rate	2.842***
	(0.474)
Median Household Income	1.83e-05***
	(3.52e-06)
Average Commute to Work (in Min)	0.00923
	(0.00645)
Foreign-born Population	-1.194
	(1.117)
Constant	18.05***
	(0.885)
Observations	768
R-squared	0.998

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

For the coefficient of interest to be a valid estimate of the causal effect of the treatment, the dependent variable should be trending in parallel. Below, I display the plots of Minnesota's monthly ridership over time and the average monthly ridership over time for the eight other states in the control group.





The red line represents October 2008, the month Minnesota finished its string of tax hikes, and the black line is a linear best-fit line. From these plots, it seems like the trends prior to the Minnesota gas tax are not exactly parallel but are fairly close to it.

6. Conclusion

In this paper, I estimate the cross-price elasticity of transit usage with respect to gas prices. I also examine how the introduction of Uber affected these elasticities and how the elasticity with respect to gas taxes differs from that with respect to ordinary gas prices.

I estimate the cross-price elasticity of transit usage with respect to gas prices to be 0.025 using city-level data and 0.0548 with state-level data as an instrument, though I find that it differs between modes of transportation and cities. These results suggest that gas prices influence transit usage, but the effect is likely not as substantial as the size of transit fares. I also find that the medium- and long-term elasticity may be larger than the short run elasticity. This is in line with prior estimates, such as by Iseki and Ali (2015), which estimated a short-term cross-price elasticity of 0.06 and found higher medium- and long-term elasticities. One limitation of my work is that these estimates are based off data aggregated at the monthly level. For example, consider a month where people take transit at higher rates when gas prices are high and take transit at lower rates when gas prices are low. Aggregating this data could lead to underestimating the effect. Since gas prices can fluctuate frequently, data on transit ridership at the weekly or daily level for many cities might produce more accurate estimates.

I also examine the impact of Uber on this cross-price elasticity. Using data from the period between 2010 and 2014 and comparing the elasticities in areas where Uber had entered and areas where Uber had yet to enter, I found no evidence of Uber affecting the elasticity. However, this result does not rule out the possibility of Uber affecting the elasticity only becoming more prominent years after entering a city. Future research could look at Uber penetration into various markets along with the relationship between gas prices and public transit ridership to get more insight into this issue.

While there is a theoretical and empirical basis to expect that the elasticity would be different for price changes due to gas taxes and price changes for other reasons, I find mixed evidence for this. A regression with annual data from all 50 states on gas taxes and transit usage resulted in a negative elasticity, though this framework likely suffers from over-aggregation, a small effective sample size, and a lack of precision. However, a difference-in-differences regression using monthly ridership data and a 2008 gas tax increase in Minnesota provides contrary evidence that gas taxes can raise transit ridership. More research on this issue is needed, and future state gas tax increases or a substantial increase in the federal gas tax for the first time since 1993 would be interesting developments to monitor.

The world has changed dramatically from the time I began this paper to now. In many places, taking public transit is seen as unsafe due to the COVID-19 pandemic, and it is unclear when their perception will change. Also, oil prices in late April 2020 reached unprecedentedly low – and even negative – levels (this has, however, inspired some to call for higher gas taxes). At least in the immediate future, the fallout from these events will likely outweigh any of the effects discussed in this paper by a wide margin.

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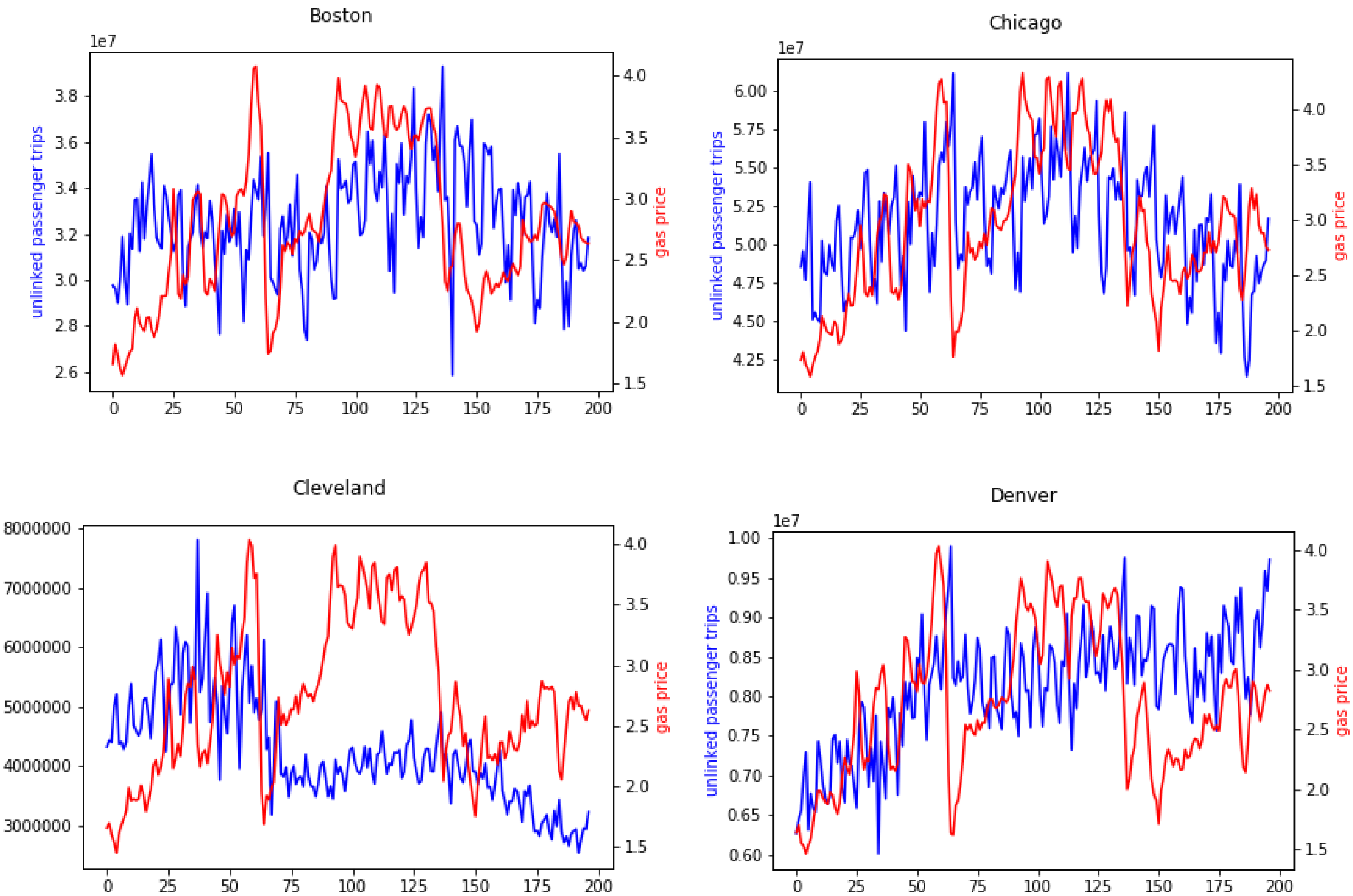
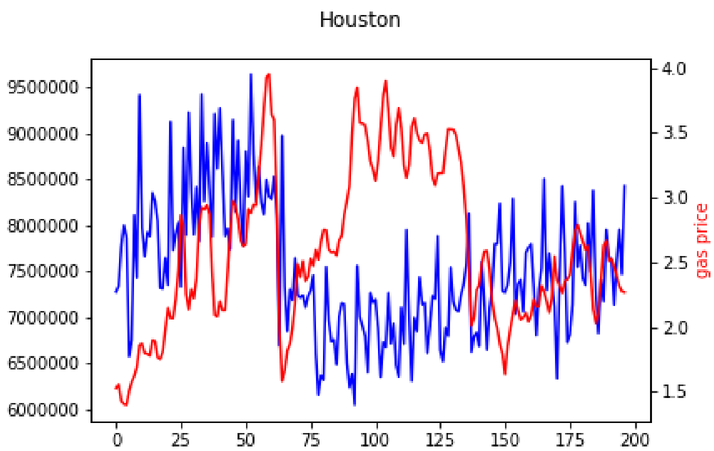
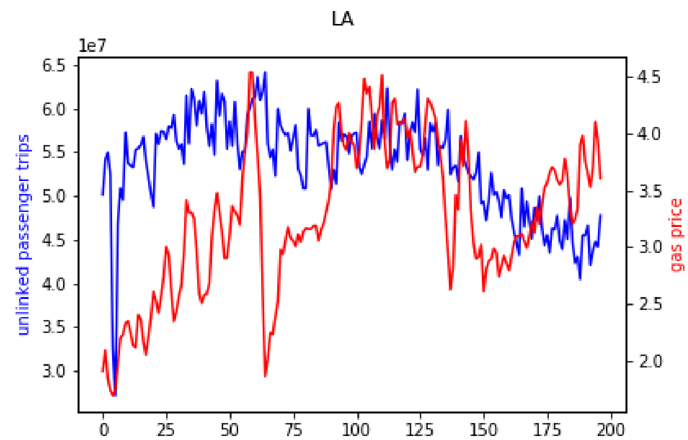
Appendix

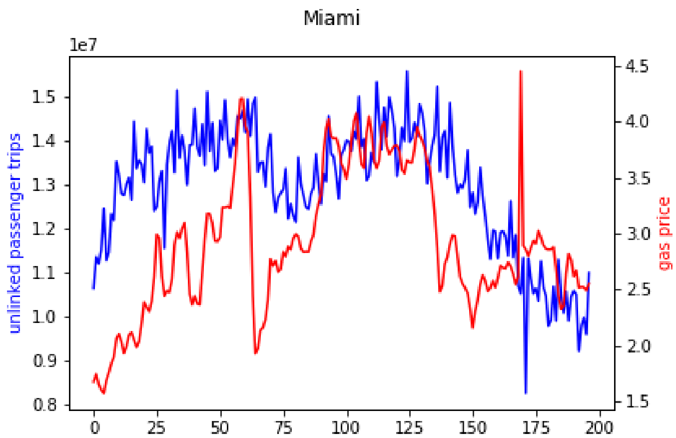
Appendix A.1. Monthly average gas price and public transit passenger trips

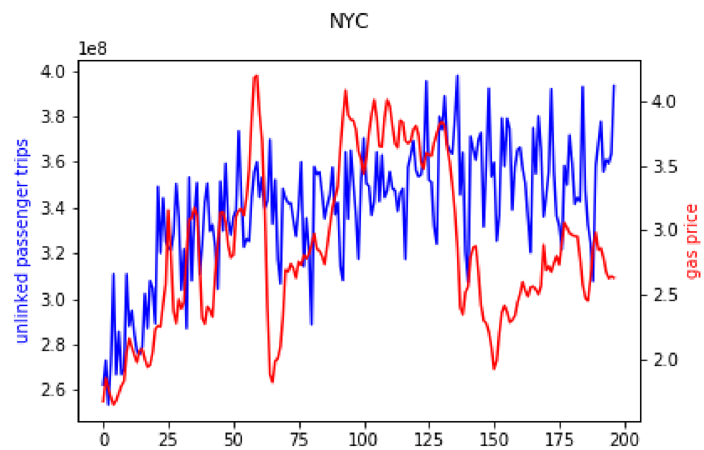
Data from National Transit Database and US Energy Information Administration

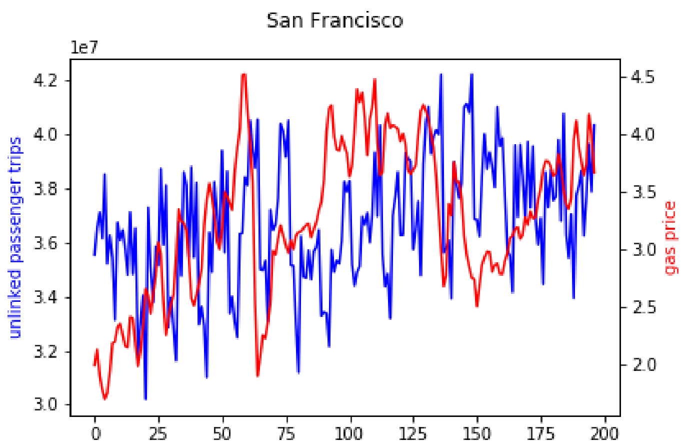


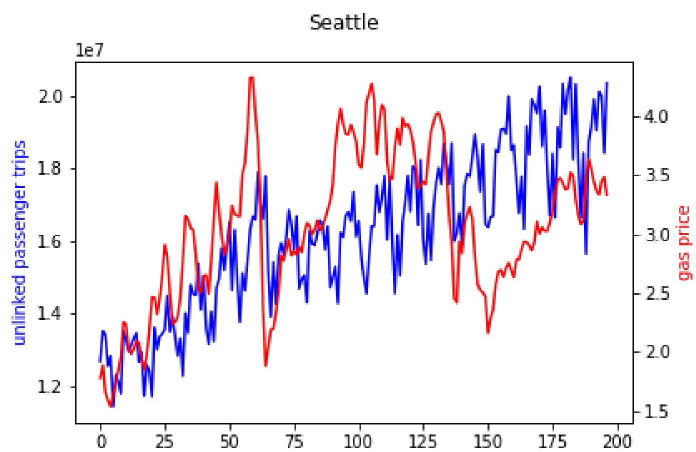

Houston
gas price


LA
1e7
unlinked passenger trips
gas price


Miami
1e7
unlinked passenger trips
gas price

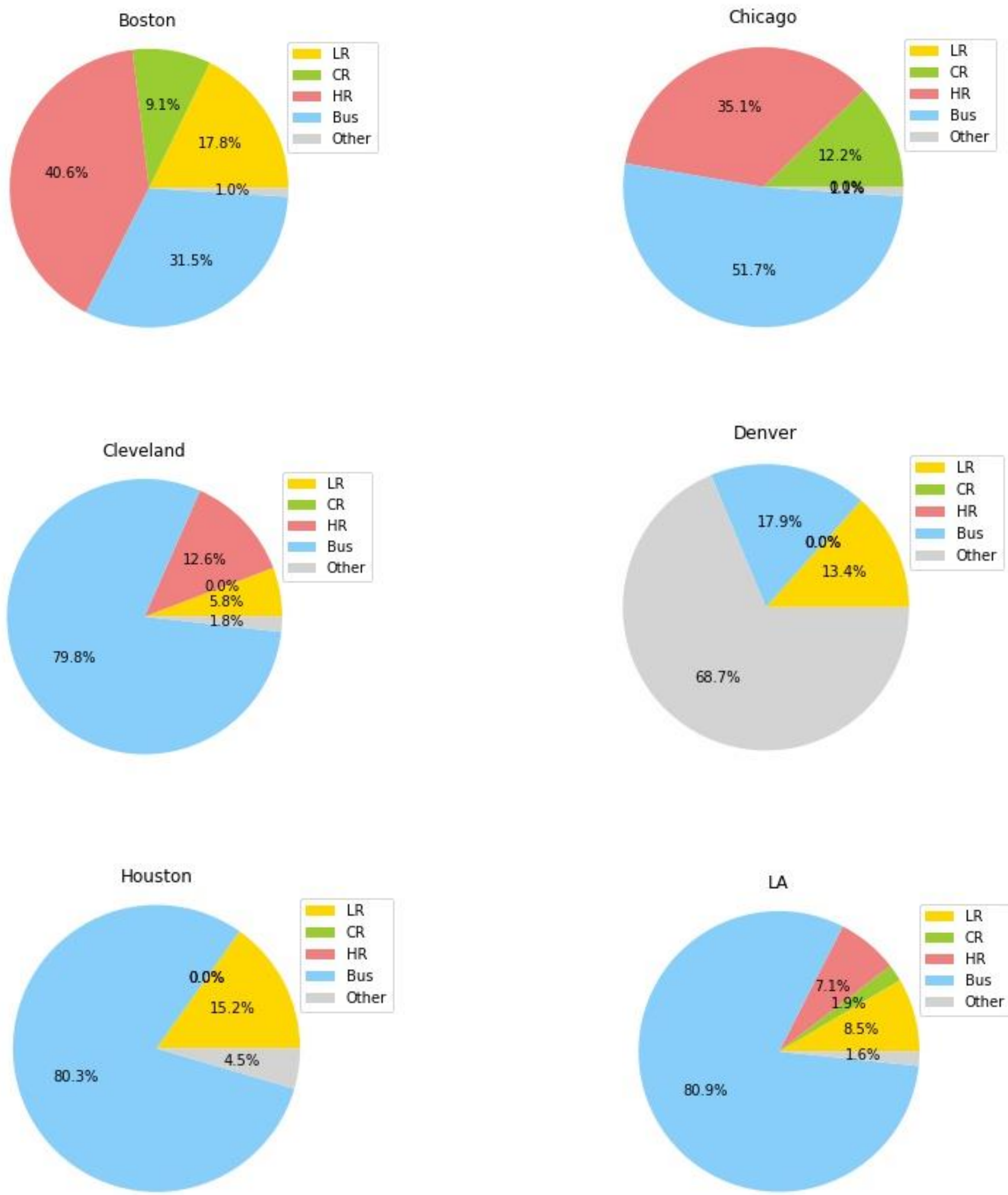

NYC
1e8
unlinked passenger trips
gas price

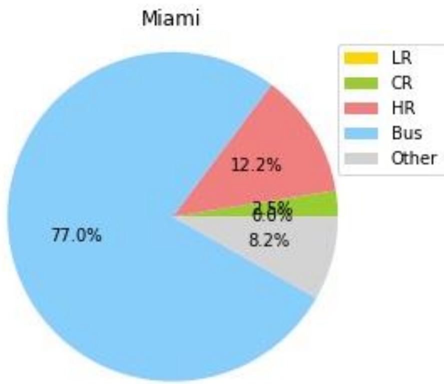

San Francisco
1e7
unlinked passenger trips
gas price

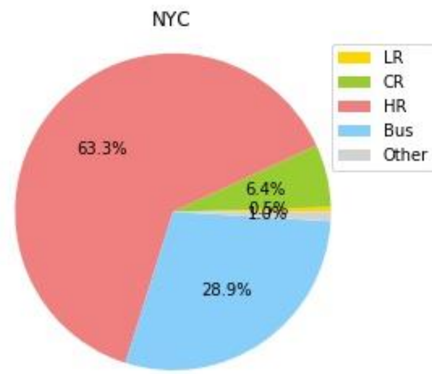

Seattle
1e7
unlinked passenger trips
gas price

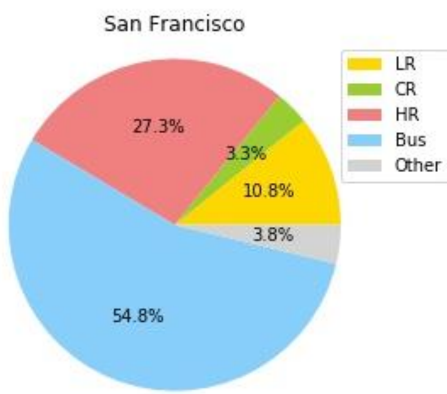
Appendix A.2. Proportion of each mode of transit by city

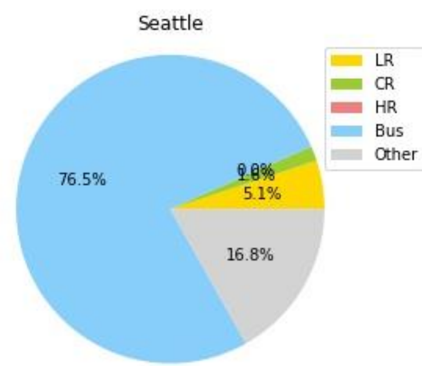
Data from National Transit Database




Miami
LR
CR
HR
Bus
Other
12.2%
2.5%
0.0%
77.0%
8.2%


NYC
LR
CR
HR
Bus
Other
63.3%
6.4%
0.5%
1.0%
28.9%


San Francisco
LR
CR
HR
Bus
Other
27.3%
3.3%
10.8%
3.8%
54.8%


Seattle
LR
CR
HR
Bus
Other
76.5%
5.1%
16.8%

Appendix A.3. Table of State Fuel Tax Rates (in cents per gallon)

Data from Federal Highway Administration

STATE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Alabama	18	18	18	18	18	18	18	18	18	18	18	18
Alaska	8	8	8	8	8	8	8	8	8	8	8	8
Arizona	18	18	18	18	18	18	18	18	18	18	18	18
Arkansas	21.5	21.5	21.5	21.5	21.5	21.5	21.5	21.5	21.5	21.5	21.5	21.5
Cali	18	18	18	18	35.3	35.7	36	40	40	30	30	42
California	18	18	18	18	35.3	35.7	36	40	40	30	30	42
Colorado	22	22	22	22	22	22	22	22	22	22	22	22
Connecticut	25	25	25	25	25	25	25	25	25	25	25	25
Delaware	23	23	23	23	23	2	23	23	23	23	23	23
Dist. of Col.	20	20	20	23.5	23.5	23.5	23.5	24	24	24	24	24
Florida	14.9	15.3	15.6	16.1	16	16.2	16.6	17	17	17	17	17
Georgia	7.5	7.5	7.5	7.5	7.5	7.5	7.5	8	8	26	26	26
Hawaii	16	17	17	17	17	17	17	17	17	17	16	16
Idaho	25	25	25	25	25	25	25	25	25	32	33	33
Illinois	19	19	19	19	19	19	19	19	19	19	19	19
Indiana	18	18	18	18	18	18	18	18	18	18	18	29
Iowa	20.7	21	21	21	21	21	21	21	21	30.8	31.7	31.5
Kansas	24	24	24	24	24	24	24	24	24	24	24	24
Kentucky	19.7	21	22.5	24.1	25.6	26.4	28.5	31	31	25	25	25
Louisiana	20	20	20	20	20	20	20	20	20	20	20	20
Maine	26.8	27.6	28.4	29.5	29.5	29.5	30	30	30	30	30	30
Maryland	23.5	23.5	23.5	23.5	23.5	23.5	23.5	24	24	32	34	34
Massachusetts	21	21	21	21	21	21	21	24	24	24	24	24
Michigan	19	19	19	19	19	19	19	19	19	19	19	26
Minnesota	20	20	22.5	27.1	27.5	28	28.5	28.5	28.5	28.5	28.5	28.5
Mississippi	18.4	18.4	18.4	18.4	18.4	18.4	18.4	18	18	18	18	18
Missouri	17	17	17	17	17	17	17	17	17	17	17	17
Montana	27.75	27.75	27.75	27.75	27.75	27.75	27.75	28	28	28	28	32

Nebraska	27.1	27	26	26.4	27.1	26.3	26.2	26.3	26.3	26.1	26.7	27.9
Nevada	24	24	24	24	24	24	24	24	24	24	24	24
New Hampshire	19.6	19.6	19.6	19.6	19.6	19.625	19.625	20	20	24	24	24
New Jersey	10.5	10.5	10.5	10.5	10.5	10.5	10.5	11	11	11	38	37
New Mexico	18.9	18.9	18.9	18.9	18.9	18.9	18.9	18.9	18.9	17	17	17
New York	23.95	24.65	24.45	25.15	24.35	25.05	25.85	27	27	26	25	24
North Carolina	29.9	29.95	30.15	30.15	32.15	35.25	37.95	38	38	36	34	35
North Dakota	23	23	23	23	23	23	23	23	23	23	23	23
Ohio	28	28	28	28	28	28	28	28	28	28	28	28
Oklahoma	17	17	17	17	17	17	17	17	17	17	17	17
Oregon	24	24	24	24	24	30	30	30	30	30	30	30
Pennsylvania	31.2	31.2	30	30	31.2	31.2	31.2	31	31	51	50	58
Rhode Island	30	30	30	30	32	32	32	32	32	33	33	33
South Carolina	16	16	16	16	16	16	16	16	16	16	16	18
South Dakota	22	22	22	22	22	22	22	28	28	28	28	30
Tennessee	20	20	20	20	20	20	20	20	20	20	20	24
Texas	20	20	20	20	20	20	20	20	20	20	20	20
Utah	24.5	24.5	24.5	24.5	24.5	24.5	24.5	25	25	25	29	29
Vermont	19	20	21	20	20	20	20	19	19	19	31	31
Virginia	17.5	17.5	17.5	17.5	17.5	17.5	17.5	11	11	16	16	16
Washington	34	36	37.5	37.5	37.5	37.5	37.5	37.5	37.5	44.5	49.4	49.4
West Virginia	27	31.5	32.2	32.2	32.2	32.2	33.4	34.7	34.7	34.6	33.2	35.7
Wisconsin	29.9	30.9	30.9	30.9	30.9	30.9	30.9	30.9	30.9	30.9	30.9	30.9
Wyoming	14	14	14	14	14	14	14	24	24	24	24	24
State Average	20.3	19.25	20.48	20.78	21.82	21.38	21.63	21.9	22.56	25.04	25.06	27.6

Appendix B.1. Baseline regression with various combinations of fixed effects

VARIABLES	(1) No FE	(2) All FE	(3) Month Year FE	(4) City Year FE	(5) City Month FE	(6) City FE
log(Gas Price)	0.433***	-0.0244	0.287***	-0.00237	0.0252**	0.0314**
	(0.0414)	(0.0164)	(0.0548)	(0.0166)	(0.0124)	(0.0131)
Population Density	0.000137***	-1.36e-05	0.000164***	-1.40e-05	-5.01e-06	-4.82e-06
	(6.02e-06)	(1.15e-05)	(5.24e-06)	(1.32e-05)	(9.75e-06)	(1.10e-05)
Population under 18	-3.100***	0.864**	-2.939***	0.871*	0.490	0.520
	(0.439)	(0.415)	(0.378)	(0.477)	(0.374)	(0.421)
Population over 55	-9.156***	-3.412***	-5.241***	-3.426***	-4.045***	-4.026***
	(0.361)	(0.488)	(0.359)	(0.561)	(0.384)	(0.432)
Unemployment Rate	1.565***	0.870***	2.429***	0.868***	-0.306**	-0.310**
	(0.331)	(0.205)	(0.366)	(0.235)	(0.137)	(0.154)
Median Household Income	1.70e-05***	4.91e-06***	2.44e-05***	4.84e-06***	2.74e-06***	2.76e-06***
	(1.30e-06)	(6.20e-07)	(1.18e-06)	(7.11e-07)	(4.61e-07)	(5.19e-07)
Average Commute to Work (in Min)	0.0791***	0.00415	0.0837***	0.00401	0.0126***	0.0126***
	(0.00668)	(0.00284)	(0.00576)	(0.00327)	(0.00286)	(0.00322)
No Vehicle HH	0.883***	1.030***	-0.233**	1.010***	1.436***	1.399***
	(0.128)	(0.250)	(0.117)	(0.287)	(0.256)	(0.287)
Foreign-born Population	1.787***	-0.339	1.464***	-0.315	-0.459*	-0.450
	(0.0848)	(0.263)	(0.0768)	(0.302)	(0.249)	(0.280)
Constant	14.18***	17.16***	13.34***	17.22***	17.10***	17.15***
	(0.176)	(0.203)	(0.154)	(0.233)	(0.177)	(0.199)
Observations	1,560	1,560	1,560	1,560	1,560	1,560
R-squared	0.936	0.996	0.958	0.995	0.996	0.995

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

Appendix B.2. Inflation-adjusted estimates

This table shows the results of the baseline regression with real gas prices (adjusted for inflation with the CPI) instead of the nominal gas prices reported by EIA. These results indicate that adjusting for inflation does not make a major difference in the estimation.

	(1)	(2)
	r1	r2
VARIABLES	log(UPT)	log(UPT)
log(Gas Price)	0.0232*	
	(0.0123)	
log(Real Gas Price)		0.0270**
		(0.0117)
Constant	17.08***	17.09***
	(0.143)	(0.143)
Observations	1,560	1,560
R-squared	0.996	0.996

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

Appendix B.3. Regression split between High Transit and Low Transit cities

	(1)	(2)
VARIABLES	High Transit	Low Transit
log(Gas Price)	0.0486***	0.0281*
	(0.0163)	(0.0157)
Population Density	-6.38e-05***	3.79e-05*
	(1.28e-05)	(2.20e-05)
Population under 18	0.869*	-0.0493
	(0.514)	(0.511)
Population over 55	0.0781	-5.715***
	(0.535)	(0.511)
Unemployment Rate	0.640***	-0.547***
	(0.212)	(0.165)
Median Household Income	4.93e-06***	1.25e-06**
	(6.89e-07)	(6.08e-07)
Average Commute to Work (in Min)	0.0203***	0.0136***
	(0.00472)	(0.00372)
No Vehicle HH	2.190***	0.0541
	(0.324)	(0.366)
Foreign-born Population	-1.390***	-0.660*
	(0.333)	(0.372)
Constant	16.18***	18.11***

	(0.261)	(0.400)
Observations	624	936
R-squared	0.998	0.995

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

Appendix B.4. Mode-differentiated regressions with state gas price as IV

VARIABLES	(1) Light Rail	(2) Heavy Rail	(3) Commuter Rail	(4) Bus
Log(State Gas Price)	0.187***	0.0805***	0.110***	0.0428***
	(0.0615)	(0.0176)	(0.0198)	(0.0136)
Population Density	0.000935***	6.71e-05***	0.000111***	-1.30e-06
	(6.69e-05)	(1.31e-05)	(1.44e-05)	(1.08e-05)
Population under 18	20.64***	-2.142***	0.770	5.142***
	(1.908)	(0.625)	(0.693)	(0.413)
Population over 55	10.05***	-1.595***	-2.949***	-1.881***
	(1.861)	(0.612)	(0.722)	(0.424)
Unemployment Rate	4.764***	-1.185***	-0.279	0.623***
	(0.706)	(0.203)	(0.244)	(0.151)
mhinc	7.70e-06***	1.10e-06*	7.22e-06***	-9.90e-07*
	(2.36e-06)	(6.33e-07)	(6.90e-07)	(5.11e-07)
avg_commute	0.0230	0.00658*	0.0323***	0.0216***
	(0.0149)	(0.00394)	(0.00516)	(0.00316)
No Vehicle HH	6.909***	2.530***	3.920***	1.584***
	(1.316)	(0.392)	(0.426)	(0.285)
Foreign-born Population	1.476	-0.0812	-4.294***	0.400
	(1.227)	(0.365)	(0.398)	(0.276)
Constant	-1.262	15.46***	12.88***	14.24***
	(0.870)	(0.334)	(0.352)	(0.195)
Observations	1,248	1,092	1,092	1,560
R-squared	0.908	0.997	0.995	0.995

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

Appendix B.5. Alternative specification for Uber entry regression

VARIABLES	(1) log(UPT)
Pre-Uber	0.0160
	(0.0123)
Post-Uber	0.0571***
	(0.0133)
Population Density	-1.57e-05
	(9.79e-06)
Population under 18	0.842**
	(0.374)
Population over 55	-4.471***
	(0.386)
Unemployment Rate	-0.170
	(0.137)
Median Household Income	2.19e-06***
	(4.65e-07)
Average Commute to Work (in Min)	0.00972***
	(0.00287)
No Vehicle HH	1.563***
	(0.254)
Foreign-born Population	-0.616**
	(0.247)
Constant	17.30***
	(0.177)
Observations	1,560
R-squared	0.996

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

I pledge my honor this paper represents my own work in accordance with University regulations

Jack Graham