Syracuse University

SURFACE

Dissertations - ALL

SURFACE

May 2018

THE EFFECT OF URBAN TRANSPORTATION SYSTEMS ON EMPLOYMENT OUTCOMES AND TRAFFIC CONGESTION

Jindong Pang

Syracuse University

ABSTRACT

This dissertation comprises two papers that examine the effect of urban transportation systems on employment outcomes and traffic congestion. The first paper evaluates the labor market effects of subway systems on low-skilled workers. A model of labor supply predicts that this should improve search and employment outcomes. The empirical findings confirm that improved subway access increases low-skilled labor force participation. Related effects for light rail and bus service are much smaller. For low-skilled men without a car, a 10 percent expansion in subway, rail, and bus service increases labor force participation by 3.0, 0.3, and 0.3 percentage points, respectively. Improved subway service increases hourly wage, but has no significant effect on work hours and commuting time. These findings confirm that subway access increases travel speed and has potential to expand the geographic scope of workers' labor market.

The second paper investigates the effects of subway expansions on passenger miles traveled (PMT) in subways and vehicle miles traveled (VMT) on roads in the US. Drawing on a panel dataset that tracks city-level expansions of subway and road systems, estimates indicate that the fundamental law of subway congestion holds as the PMT increases one for one with the length of the subway systems. Subway systems have substitution and growth effects on road traffic. A 10 percent expansion of a subway system reduces contemporaneous traffic on ring interstate highways and non-highway arterial roads by 0.7 percent and 1.4 percent, respectively. With a three-year lag, a 10 percent increase in subway capacity increases VMT on ring highways by 0.4 percent and increase VMT on radial highways by 1.7 percent. Together, these estimates suggest that subway expansions do not reduce congestion on radial highways but do relieve congestion on roads that are close substitutes to subways (ring highways and non-highway arterial roads).

THE EFFECT OF URBAN TRANSPORTATION SYSTEMS ON EMPLOYMENT OUTCOMES AND TRAFFIC CONGESTION

by

Jindong Pang

B.S., Xi'an Jiaotong University, 2011
M.S., Xi'an Jiaotong University, 2013

Dissertation

Submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in *Economics*.

Syracuse University

May 2018

ACKNOWLEDGEMENTS

I thank my advisor Stuart Rosenthal for his valuable guidance and suggestions. I appreciate the help from Alfonso Flores-Lagunes and Michael Wasylenko for my job market. I am also grateful for comments from Marco Gonzalez-Navarro, Hugo Jales, Matthew Kahn, Jeffrey Kubik, Leonard Lopoo, Jordan Rappaport, Jonathan Rothbaum, Krieg Tideman, and Yulong Wang. I appreciate the classes instructed by Badi Baltagi, William Horrace, Leyla Karakas, Yoonseok Lee, Jan Ondrich , Amy Schwartz, Perry Singleton, and John Yinger.

I would like to acknowledge the assistance from Peg Austin, Karen Cimilluca, Emily Henrich, Sue Lewis, Candi Patterson, Mary Santy, Laura Walsh, Katrina Wingle, Matthew O'Keefe, and other staff in the Economics Department and Center for Policy Research.

Lastly, I would like to thank my family and friends for their support. My parents Xiujyu Cui and Kunzhen Pang have devoted decades in helping me pursue my academic career. I thank my wife Shulin Shen for supporting me in our years at Syracuse. My daughter Evelyn offers me lots of pleasure and happiness. I appreciate my mother-in-law Xiaoqiu Li for taking care of the baby. Thanks to all friends and classmates and I have enjoyed the time at Syracuse.

TABLE OF CONTENTS

LIST OF FIGURES

Chapter 2: Do Subways Improve Labor Market Outcomes For Low-Skilled Workers?

Chapter 3: Do Subways Reduce Congestion? Evidence from US Cities

LIST OF TABLES

Chapter 2: Do Subways Improve Labor Market Outcomes For Low-Skilled Workers?

Chapter 3: Do Subways Reduce Congestion? Evidence from US Cities

Chapter 1: The Effect of Urban Transportation Systems on Employment Outcomes and Traffic Congestion

Urban transportation systems are central to city formation and urban development, and changes in transportation systems are likely to affect every aspect of people's lives. There has been an emerging literature studying the effect of highway systems on city growth, suburbanization, inter-city trade, and regional development. However, there exists limited evidence on the role of public transit on economic activities and individuals' behaviors. The two papers in this dissertation aim to evaluate the effect of public transit, especially subway systems, on low-skilled employment outcomes and urban traffic congestion.

Subway systems are heavily subsidized by government revenue, as the ticket revenue cannot cover the enormous capital and operating costs. There is an ongoing debate on the efficiency of these subsidies. Opponents of transit projects believe that transit systems reduce welfare and cannot pass the cost-benefit analysis. On the other side of the debate, supporters state that there are important public good aspects to public transit and that public transit also has potential to address a host of negative externalities. The two papers in this dissertation provide more evidence for the debate by estimating the benefits of subway systems in improving low-skilled employment outcomes and in reducing traffic congestion. While subway systems are expensive to build, they also have higher speed, larger capacity, and possibly the largest benefit.

The first paper in chapter 2 builds on the fact that many low-skilled individuals in the US cannot afford automobiles. About 18% of the individuals with less than a high school degree do not have access to an automobile in 2014 while this number is only 4 percent for people with a college degree or above. The much more limited ability of low-skilled workers to own a vehicle increases their reliance on public transit. That in turn contributes to the disproportionate concentration of low-income families in city centers where public transit is more cost effective (because of higher density) and more accessible. Improvements in subway systems could increase the travel speed of low-skilled workers, extend the geographic scope of their labor market, and give them access to better job opportunities. I propose a simple model of labor supply in which an increase in travel speed increases search and improves the quality of an individual's labor market outcomes. The predictions of the model are tested by analyzing a merged data set with both the information on workers' employment outcomes and the information on city-level changes of subway, light rail and bus systems over time. The empirical evidence confirms that subway access significantly increases both the tendency for low-skilled individuals to work and their wages. However, the regression results show that the effect of subway access on work hours and commuting times is not significant.

The second paper in chapter 3 evaluates the impact of subway expansions on subway ridership and traffic on different types of roads. Congestion on urban road systems has been rising in U.S. cities in recent years. The annual delay from congestion on urban road systems cost commuters in 471 urban areas in 2014 roughly 42 hours, which was up sharply from 1982 for which the corresponding estimate was just 18 hours. One policy response to this congestion problem is "building your way out of congestion". This approach, however, is not effective to reduce congestion because of the fundamental law of road congestion, which states that the elasticity of road traffic with respect to road capacity is at least one. Another proposed method to alleviate road congestion is public transit. The current literature, however, has not reached consensus on the role of subway systems in congestion relief. By analyzing a panel data set with 14 cities in 24 years, this paper shows that the passenger miles travelled in subways increases one for one with the length of the subway systems. I also show that subway expansions could reduce traffic on ring interstate highways (3-digit interstate highways) and non-highway arterial roads, but increase traffic on radial highways (1- or 2-digit interstate highways). The reducing effect is consistent with the intuition that improved subway services will make people switch from driving to transit riding. The increasing effect might come from the decentralization effect of subway systems on city population.

Chapter 2: Do Subways Improve Labor Market Outcomes For Low-Skilled Workers?

Jindong Pang

Department of Economics

Syracuse University

1. Introduction

It is widely appreciated that low-skilled workers[1] are often too poor to afford a vehicle. Average annual earnings among household heads with less than a high school degree, for example, are $16,447 and 18 percent of these individuals do not own cars.[2] The corresponding numbers for those with a college degree are $71,648 and just 4 percent, respectively. The much more limited ability of low-skilled workers to own a vehicle increases their reliance on public transit. That in turn contributes to the disproportionate concentration of low-income families in city centers where public transit is more cost effective (because of higher density) and more accessible (Glaeser et al., 2008; Brueckner and Rosenthal, 2009). Nevertheless, while these and related characteristics of low-skill urban residents are known, the effects of public transit, and especially the type of public transit, on labor market opportunities for the poor has been overlooked. This paper begins to fill that gap.

I propose a simple model of labor supply in which an increase in travel speed increases search and improves the quality of an individual's labor market outcomes. An implication of this model is that it is important to distinguish among alternate modes of public transit when considering the impact of public transit on the labor market opportunities of the poor. That is because subways travel at far higher speeds relative to above ground light rail and bus systems. Drawing on a panel dataset that tracks expansions to subway, light rail and bus systems over time, I examine this and other related questions. To anticipate, evidence confirms that subway access significantly increases both the tendency for low-skilled individuals to work and their

[1] The low-skilled workers are individuals with less than a high school degree (less than high school completion). Less-educated, low-skilled, and low levels of education are used interchangeably.
[2] The calculation is for low-skilled household heads whose ages are between 25 and 60 in 2014 American Community Survey. For low-skilled individuals living in cities, 32 percent of them do not have access to private vehicles while this number is 16 percent for highly educated workers.

wages. In contrast, expanding light rail and bus systems has a much smaller effect on the labor market outcomes of low-skilled individuals.

Low-income families are more likely to live in central cities. Schuetz et al. (2017) document that central cities in 24 large US MSAs tend to be poor and non-white after analyzing the 2010-2014 American Community Survey (ACS) data. The stylized fact that low-income families are concentrated in central cities is not consistent with the prediction of the standard Alonso-Muth-Mills urban model. Glaeser et al. (2008) show that the urbanization of poverty comes mainly from better access to public transportation in central cities. The presence of public transit is also highly predictive of whether low-income households will reside in a specific neighborhood (Brueckner and Rosenthal, 2009). Table A1 reveals that compared with people with a high school degree or above, low-skilled individuals are more likely to live in the central or principle cities of a MSA. A cross sectional analysis indicates that cities with better transit services are more likely to have high proportions of low-skilled individuals and low labor force participation (LFP) rates (see Table A2).

Subway construction is controversial because of its enormous cost. As an example, the cost of building the Second Avenue Subway in New York City, the first phase of which opened on January 1, 2017, is roughly $2.1 billion per mile.[3] Ticket fare revenue also typically does not cover operating expenses for subway systems (APTA, 2014). In 2014, for example, fare revenue only covered 41 percent of operating expenses for the New York City subway system (National Transit Database). Most capital and operation funding gaps are filled by government subsidies. In 2014, subsidies for all forms of public transit from all levels of governments amounted to $44 billion (National Transit Database). Despite these enormous subsidies, public transit only

[3] The cost number is from: https://www.thoughtco.com/rail-transit-projects-costs-2798796

accounts for 1 percent of total passenger miles traveled (DOT, 2011). Winston and Maheshri (2007) compare the sum of consumer surplus and benefits in congestion reduction with the level of government subsidy for rail systems in 25 US cities. They conclude that these rail systems reduce welfare and cannot pass the cost-benefit analysis.

On the other side of the public transit debate, supporters of transit projects state that there are important public good aspects to public transit and that public transit also has potential to address a host of negative externalities.[4] These include opportunities to reduce auto congestion on the city roads (Anderson, 2014) and reduce air pollution in cities (Gendron-Carrier et al., 2017). Parry and Small (2009) construct a structure model to study the optimal transit subsidy. This model accounts for benefits from reduced congestion, pollution, and traffic accidents. They find that fare subsidies for rail and bus transit systems in Washington, DC, Los Angeles, and London are welfare improving.

If subway access has a notable positive effect on employment opportunities for the poor, that effect would add to arguments in favor of the provision and expansion of subway systems. From this perspective, the possibility exists that subway systems should be partly viewed as implicit net transfer programs that are funded by middle and upper income tax payers while providing disproportionate benefits for low-income families and low-skilled workers.

Few studies analyze the impact of subway systems on employment outcomes. Sanchez (1999) makes the first attempt and finds people in residential census blocks that have rail or bus access in Portland and Atlanta are more likely to work. Holzer et al. (2003) study the expansion of San Francisco Bay Area's rail system, and they find hiring of Latinos increases in areas near

[4] See Litman (2007) and Litman (2015) for reviews.

the new transit stations. These earlier studies suffer from external validity problems because they only focus on one or several cities. These early results may not have identified a causal relationship between transit access and labor supply because individuals who want to work may sort into neighborhoods with better transit services.

Subway systems have the potential to mitigate disparities between where low-skilled workers live and where their employment opportunities may be found by enabling low-skilled workers to search more extensively over longer distances. This idea implicitly forms part of the foundation of an extensive literature on spatial mismatch which, in its original context, emphasized that reduced proximity to employment contributes to economic strife and reduced opportunities (Kain, 1968; Rosenbaum, 1995; Blumenberg and Ong, 1998; Gobillon et al., 2007; Hellerstein et al., 2014). Measures improving the accessibility to jobs help the low-skilled workers. For example, the employment outcomes of low-skilled workers are improved by programs that provide housing opportunities for low-income families in neighborhoods outside of the central city (Rosenbaum, 1995). Other studies have shown that private vehicle ownership improves employment outcomes (Raphael and Rice, 2002; Ong, 2002; Baum, 2009). Subway service can be another effective measure to connect workers and jobs.

This paper offers two primary contributions to the existing literature. To the author's knowledge, it is the first to identify the causal effects of subway expansions on labor market outcomes of low-skilled workers using data that represents the continental US. The second contribution is that this paper evaluates and compares the effects of subway, bus, and rail systems on labor market outcomes for low-skilled workers. Compared with light rail and bus transit, subway transit has the most prominent benefits, consistent with its faster travel speed.

The effects of public transit on labor market outcomes among low-skilled workers should be considered in future policy debates about the costs and benefits of public transit.

To identify the effects of subway systems on low-skilled employment outcomes, I merge Census 1990, Census 2000, and American Community Survey 2005-2014 individual-level data with a city-level panel dataset that tracks the changes of public transit services for US cities. The merged dataset has 12 cities that have subway services, 36 cities that have subway or light rail systems, and 161 cities that have bus services. Individuals' labor market outcomes are regressed on demographic characteristics, city transit services, time-varying city attributes, city fixed effects, and year fixed effects. The identification of the effects of transit services comes from the city-level variation of transit services over time. Private vehicle ownership for each individual is endogenous to employment outcome variables. I use a reduced form OLS specification, the instrumental variable method, and a sample selection model to solve this issue. All three methods show quantitatively similar results.

The empirical findings are consistent with the predictions of the conceptual model. For less-educated men without private vehicles, a 10 percent expansion in subway, rail, and bus systems increases their labor force participation by 3, 0.3, and 0.3 percentage points, respectively. The impact of subway systems on LFP is the largest. All transit modes have a smaller and insignificant effect on LFP for workers who own private vehicles, consistent with the intuition that households who own vehicles are less likely to use transit services. The labor supply benefit of subway expansions mainly lies in the extensive margin of labor supply, as the effect on hours worked per week is not statistically significant. Subway expansions enhance wages. This finding implies that higher travel speeds lead to longer commutes, which in turn allow workers to commute to jobs that offer higher wages. No significant effect is found for commuting times, supporting the view that subway expansions do not reduce commuting times but rather extend the geographic scope of labor market.

The rest of the paper is organized in the following sections. A theoretical labor supply model is built in section 2 and the predictions of the model provide guidance for empirical work. Section 3 introduces data and summary statistics. Section 4 discusses the empirical strategy to identify the effects of transit on labor market outcomes. The regression results are analyzed in section 5. Section 6 concludes.

2. A Theoretical Model

This section outlines a simple model of labor supply to study the effect of a higher transit speed on employment outcomes. Improved public transit increases travel speed for low-skilled workers who may not have sufficient means to own an automobile. Higher transit speeds could increase the geographic scope of the individual's labor market and improve labor market outcomes. The implications of higher speeds for LFP, work hours, commuting distance, and wages are evaluated below.

Consider the following static labor supply model. [5] The utility of a representative agent depends on income y and leisure $l{:}U(l,y)$. The utility function satisfies the traditional properties (decreasing marginal utility, and $\frac{\partial U}{\partial y \partial l} > 0$). The budget constraints are:

$$y = w(u)h$$

[5] I assume that people do not relocate in this model. Given that many low-skilled workers are trapped in cities and moving is costly, this assumption is not unreasonable.

$$l = T - h - \frac{u}{s}$$

The highest wage that the agent receives under commuting distance u is denoted by $w(u)$. s is commuting speed and $t = \frac{u}{s}$ denotes commuting time. h is work hours. T is total time endowment.

2.1 The effect on labor force participation

A corner solution exists when individuals choose to stay out of the labor force. The budget constraints can be rewritten as one equation: $y = -w(u)l + w(u)T - w(u)\frac{u}{s}$. Figure 1 illustrates two possible effects of a higher commuting speed on LFP.

Given commuting distance u as a constant, figure 1A shows the impact of a higher commuting speed s on LFP. The budget constraint will expand from DCA to EBA after an increase in s. The agent's consumption bundle will change from point A to point O and the agent switches to work after the increase in travel speed.

Figure 1B displays the effect on tendency to work if commuting distance u becomes longer and commuting speed s is a constant. Commuting a longer distance will increase wage ($w'(u) \geq 0$) [6] and reduce time available for work and leisure, so the slope of the budget constraint becomes steeper and the horizontal intercept shrinks (from DBA to ECA). The agent will shift to work under the higher wage (from A to O).

[6] If $w'(u) = 0$, the effect of a higher speed s on LFP is illustrated in figure 1A. The intuition for $w'(u) \geq 0$ is that the maximum wage one receives should not decrease with commuting distance (searching geography) u because of better matches between jobs and workers.

If both commuting speed s and commuting distance u increase, the impact on LFP is still positive. Therefore, higher travel speeds will certainly improve tendency to work.

2.2 The effects on intensive margin outcomes

For agents who choose to work, this subsection evaluates the effects of travel speeds on the intensive margin outcome variables, including work hours, commuting distances, and commuting times.

2.2.1 Case 1. $\boldsymbol{w'(u) = 0}$

First, consider a special case when $w'(u) = 0$, i.e., the best wage offer does not rise with commuting distances. This is true for minimum-wage workers who have very limited education and human capital. For a fixed commuting distance *u*, the agent chooses *h* to maximize utility:

$$\max_h U(T - h - \frac{u}{s}, wh)$$

The effect of travel speeds on work hours can be easily derived from the first order condition and the second order condition.

$$\frac{dh}{ds} = -\frac{\partial^2 U}{\partial h \partial s} / \frac{\partial^2 U}{\partial h^2} > 0$$

Similarly, the impact on commuting times is:

$$\frac{dt}{ds} = -\frac{1}{s^2} < 0$$

The model predicts that higher commuting speeds will lead to longer work hours and shorter commuting times if $w'(u) = 0$.

2.2.2 Case 2. $\boldsymbol{w'(u) \geq 0}$

The maximum wage $w(u)$ that the agent receives is likely increasing in commuting distance u at a decreasing rate ($w'(u) \geq 0,\ w''(u) \leq 0$).[7] More than 60 percent of men with less than high school completion earn wages that are higher than minimum wages after 2009. [8] Many low-skilled workers have the potential to earn higher wages if they have access to more job opportunities. As one searches more extensively in geography, he or she could receive higher wage offers as a result of better matches between workers and jobs.[9]

The agent now varies both h and u to maximize utility:

$$\max_{h,u} U(T - h - \frac{u}{s}, w(u)h)$$

The effect of travel speeds on work hours, commuting time, and commuting distance are solved from the first order and second order optimization conditions. The detailed derivation is in the appendix. The effect of travel speeds on work hours is illustrated in equation (1).

$$\frac{dh}{ds} = \frac{\frac{\partial^2 U}{\partial h \partial u}\frac{\partial^2 U}{\partial u \partial s} - \frac{\partial^2 U}{\partial u^2}\frac{\partial^2 U}{\partial h \partial s}}{\frac{\partial^2 U}{\partial h^2}\frac{\partial^2 U}{\partial u^2} - (\frac{\partial^2 U}{\partial h \partial u})^2} = \frac{\frac{\partial^2 U}{\partial h \partial u} * positive + positive}{positive} \tag{1}$$

---

[7] It should be noted that $w'(u) > 0$ does not need to hold for all possible values of u. $w'(u) > 0$ should hold for at least one value of u. If $w'(u) = 0$ for all values of u, this is the case discussed in section 2.2.1.
[8] The minimum wage rates of most states are less than or equal to \$9. The 40th percentile of low-skilled men's wage is \$10.1.
[9] This assumption is maintained in Holzer et al. (1994), and is consistent with empirical evidence (Ihlanfeldt and Sjoquist, 1989; Holzer et al., 1994; Raphael and Rice, 2002; Baum, 2009).

As is shown in the appendix, the relative sizes of the substitution and income effects determine the sign of $\frac{\partial^2 U}{\partial h \partial u}$ and the sign of $\frac{dh}{ds}$. A large substitution effect makes $\frac{\partial^2 U}{\partial h \partial u}$ and $\frac{dh}{ds}$ positive. In this case, improvements in travel speed will increase work hours. If substitution effect is so small that $\frac{\partial^2 U}{\partial h \partial u}$ is far below zero and $\frac{dh}{ds}$ is negative, higher travel speeds lead to fewer work hours.

Similarly, the impact of commuting speeds on commuting distances is:

$$\frac{du}{ds} = \frac{\frac{\partial^2 U}{\partial h \partial u}\frac{\partial^2 U}{\partial h \partial s} - \frac{\partial^2 U}{\partial h^2}\frac{\partial^2 U}{\partial u \partial s}}{\frac{\partial^2 U}{\partial h^2}\frac{\partial^2 U}{\partial u^2} - (\frac{\partial^2 U}{\partial h \partial u})^2} = \frac{\frac{\partial^2 U}{\partial h \partial u} * positive + positive}{positive} \tag{2}$$

The relative sizes of the substitution and income effects still determine the sign of $\frac{du}{ds}$. The effect of commuting speeds on commuting distances cannot be directly tested empirically, as the Census data does not have information on commuting distances. An indirect method, however, is studying the influence of public transit on wages. A significantly positive effect between transit services and wages indicates that transit extends commuting distances ($\frac{du}{ds} > 0$) and wages are increasing in commuting distances ($\frac{dw}{du} > 0$).

The impact of travel speeds on commuting times is derived from $du = tds + sdt$:

$$\frac{dt}{ds} = \frac{1}{s}(\frac{du}{ds} - t) \tag{3}$$

Equation (3) indicates that travel speeds have an undetermined effect on travel times. If the higher travel speeds increase commuting distances a lot, commuting times may increase. Alternatively, commuting times will decline with travel speeds if higher speeds decrease or have zero effect on commuting distances.

The above analysis indicates that higher travel speeds will certainly improve LFP. Increases in commuting speeds will increase work hours and reduce commuting times if $w'(u) = 0$. However, the effect on work hours, commuting distances, and commuting times is uncertain under the assumption $w'(u) \geq 0$. The empirical findings that transit systems improve wages but have no significant effect on work hours and commuting distances are consistent with the assumption $w'(u) \geq 0$.

The model also indicates that subway transit is likely to have the largest impact on employment opportunities, as subway systems are faster than light rail and bus systems.[10] In addition to public transit expansions, this model can also be applied to other contexts where commuting costs decrease, including vehicle ownership and highway expansions.

3. Data

The individual level data used in this paper is from IPUMS ACS and Decennial Census (Ruggles et al., 2015). Specifically, data for 1990 and 2000 are from the decennial Census; and data for 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013 and 2014 are from ACS. The Census data only identifies cities with populations above 100,000. The level of transit services in each city in each year is from National Transit Database (NTD). The NTD data is merged to Census data by year and city. The analysis focuses on men and single women between the ages of 25 and 60.[11]

[10] The theoretical model predicts that a larger increase in travel speeds will lead to a larger impact on the employment outcome variables. In addition to travel speed, other factors might also be able to explain why subway systems have the largest effect. For example, subway systems usually serve the downtown areas and are efficient at moving people in and out of central cities. Testing which channel explains the largest effect of subway systems is beyond the scope of this paper.

[11] Compared with men and single women, the labor supply decisions of married women are more elastic and are more likely to be influenced by their partners' employment outcomes. To model the labor supply decisions of married women, one has to consider the labor supply decisions of their partners simultaneously. Solving this complexity is beyond the scope of this

The NTD was established by Congress to be the nation's primary source for information and statistics on the transit systems in the United States. Recipients or beneficiaries of grants from the Federal Transit Administration (FTA) are required by statute to submit data to the NTD. Over 660 transit providers currently report to the NTD through the Internet-based reporting system. The NTD data provides annual information on transit facilities, service levels, funding sources, revenues, and costs for Urbanized Area and for cities throughout the 1991-2014 period. In order to add the 1990 Census data to my sample, I use transit data for 1991 in the 1990 census year.

In order to compare the effects of different transit modes, three variables are constructed to represent the service levels of bus, subway, and rail transit in each city. The number of buses operated on the day of maximum service denotes the level of bus service. Subway and rail service levels are measured by total directional route miles in each city.[12] For any given travel speed, the quality of public transit riding experience depends on the degree of congestion, as congestion may increase wait times for an available ride and crowding can reduce ride comfort levels. Both concerns increase with population for a given public transit network. For that reason, public transit services for each city are measured by number of buses per 1000 people, subway miles per 1000 people, and rail miles per 1000 people.[13]

---

paper. Thus, married women are excluded from the primary analysis. I conduct similar analysis for married women without solving the two-earner labor supply problem, and the empirical results not shown here are qualitatively similar to the analysis for men and single women.

[12] These three variables are available from data. Duranton and Turner (2011) use number of buses to measure public transit service. Gonzalez-Navarro and Turner (2016) use total subway line miles to represent subway services in cities. Directional route miles refer to the mileage in each direction over which public transportation vehicles travel.

[13] The number of buses per capita or subway/rail miles per capita is very small in magnitude. Using these per capita measures leads to very large coefficients in regression analysis. In order to have moderate magnitudes for the regression coefficients, buses per 1000 people and subway/rail miles per 1000 people are used.

Table 1 displays summary statistics for transit measures. There are 12 subway cities in the US.[14] Compared with the cross sectional variation, the temporal variation in total subway miles is smaller. Most subway cities have experienced changes in their subway networks between 1991 and 2014. Table A3 shows the length of subway systems in each city from 1990 to 2014. It can be seen that Washington, DC, Chicago, Los Angeles, San Francisco, Atlanta, Baltimore, and Miami have had sizeable extensions of their subway systems during this period. These subway expansions are achieved gradually, so there are multiple changes in the length of subway systems across time. For example, the metro system in Washington, DC was 156.2 miles in 1990, then increased to 193.5 miles in 2000, and reached 211.8 miles in 2005.

There are 31 cities with light rail systems during 1991-2014.[15] The light rail measure includes the sum of miles for light rail, hybrid rail, and commuter rail that connects cities and their suburbs. The variation of rail systems over time is larger than that of subways. Hundreds of cities have bus service. Bus service has the largest variation across cities and time, as the costs of varying bus service levels are low.

Four employment outcomes are considered in this paper, including LFP, hourly wages, work hours, and commuting times. Table 2 summarizes employment outcomes for different groups of people. Compared with all workers (79%), LFP rate is lower for low-skilled men (71%). LFP is the lowest for low-skilled working-age cohorts who do not own a vehicle (49%). However, the difference in hours worked per week between low-skilled workers and all people is

[14] Los Angeles, CA, Oakland (San Francisco), CA, Washington, DC, Miami, FL, Chicago, IL, Boston, MA, NYC, NY, Baltimore, MD, Jersey City, NJ, Cleveland, OH, Philadelphia, PA, Atlanta, GA. These 12 subway cities are in 11 states. The subway systems are defined as heavy rail systems in NTD. Part of a subway system may be above ground.

[15] Little Rock, AR, Phoenix, AZ, Los Angeles, CA, Orange, CA, Sacramento, CA, San Francisco, CA, Stockton, CA, Denver, CO, Chicago, IL, New Orleans, LA, Boston, MD, Baltimore, MD, Minneapolis, MN, Charlotte, NC, Newark, NJ, Buffalo, NY, New York City, NY, Cleveland, OH, Portland, OR, Philadelphia, PA, Pittsburgh, PA, Memphis, TN, Nashville-Davidson, TN, Austin, TX, Houston, TX, Lewisville, TX, Salt Lake City, UT, Alexandria, VA, Hampton, VA, Seattle, WA.

much smaller than the difference in tendency to work. Compared with all workers, the low-skilled groups have lower wages. Unsurprisingly, average commuting time for workers who do not have access to private vehicles is longer. The low-skilled workers in general have lower wages, fewer work hours, and longer commuting times than more skilled workers do, and low-skilled working-age adults are less likely to work than their more skilled counterparts are.

4. Empirical Strategy

Two groups of individuals whose ages are between 25 and 60 are studied: men and single women with less than a high school degree. Workers with low levels of education are not likely to own vehicles and have to rely on public transit. The less-educated men are chosen as the primary focus because of their larger sample size.[16] The analysis for single women serves as a robustness check.

Transit service information is merged with multiple-year Census and ACS data. Pooling data from different years enables me to control for city and year fixed effects, which eliminate city or year time invariant unobserved factors that may bias the estimates.[17] The identification comes from the variation of transit services over time.

For worker j in city c at year t, the labor market outcomes are modeled as the following equation:

[16] Including both married men and single men in my analysis maintains a large sample, and I control for marital status in the regression. I also conduct a robustness check by studying the effect of transit on single men with less than high school completion. The regression results not shown here indicate that the results from low-skilled single men are qualitatively similar to the results using all low-skilled men.

[17] Another reason for using Census and ACS data is that they have city-level geographic information. This city-level geographic information enables me to know the city in which an individual resides. Many panel data sets, including NLSY, PSID, and SIPP, do not have city geography information.

$$E_{jct} = \beta_0 + \beta_1 S_{ct} + \beta_2 B_{ct} + \beta_3 R_{ct} + \beta_4 X_j + \beta_5 v_j + \beta_6 A_{ct} + \theta_c + \delta_t + \varepsilon_{jct} \quad (4)$$

E_{jct} represents LFP status, work hours, commuting time or wage rate. S_{ct}, B_{ct}, and R_{ct} are average measures for subway, bus, and rail services. X_j is a vector of individual characteristics, including age and its quadratic term, gender, marital status, education (less than a high school degree, high school degree or some college, college degree or above), race (white non-Hispanic, white Hispanic, Black, Asian), disability status, have children younger than 13 or not, citizenship status, number of years in the US, and English speaking skill. Interaction terms of these variables are also controlled. Thirty-two industry fixed effects are included when commuting times, work hours and wages are the left-hand side variables. The occupation earning score is included as a control variable in the regression when the dependent variable is hourly wage. v_j denotes whether the household has access to private vehicles. A_{ct} denotes time varying city characteristics, including city population, population density, percent of people with a college degree or above, percent of people with a high school degree or some college, [18] labor demand shock (Bartik shift-share instrument; Bartik, 1992), [19] state unemployment rate. θ_c and δ_t are city and year fixed effects. ε_{jct} is an error term.

An assumption for identification is that the transit variables are exogenous to the left-hand side variables after controlling for other covariates. However, there can be three threats for this assumption. First, omitted variable bias is possible. Second, transit service variables can be endogenous as cities may supply more transit services in response to poor labor market

[18] Percent of individuals without high school diploma is the omitted base group.
[19] This variable is constructed as the weighted averages of national employment growth across industries using city industry employment shares as weights. It measures local labor demand in each city in each year.

outcomes. Lastly, sorting of low-skilled workers across cities may also bias the estimates, although sorting within a city is not an issue here as the transit measures are at the city level.

There are several arguments supporting that these endogeneity issues do not drive the empirical results and the exogeneity assumption is likely to hold. First, the individual characteristics, city fixed effects, year fixed effects, and time varying covariates of cities should absorb most of the correlation between the transit variables and the error term, so omitted variable bias should be small. Second, there is little evidence showing that cities respond to workers' labor market outcomes by varying transit services. Public transit projects are usually built to solve congestion or air pollution problems, and improving employment outcomes for low-skilled workers is seldom considered as the primary purpose of these projects. Local governments usually apply federal funding to expand transit services, especially for light rail and subway systems. The distribution of federal capital funding can be inefficient and may not be correlated with local needs.[20]

Third, public transit projects, especially for subway and rail transit, take years to raise funding, design and construct.[21] Compared with the time when the project was proposed, the employment outcomes of low-skilled workers at project completion can change significantly. Local governments have little room to manipulate the openings of transit projects, which act like random shocks to the city. The transit variables are not likely to be endogenous. Fourth, I control

[20] In 2013, 42% of the capital funding comes from federal government (APTA, 2015). Berechman (2010) mentions "...the proclivity of local decision makers to accept a project regardless of its actual benefits and risks increases with the proportion of funding obtained from higher levels...Our hypothesis states that local authorities, as recipients of federal and state money, tend to regard external funding as costless and as political benefits. They are therefore predisposed to promoting infrastructure projects containing a large external funding component...this tendency promotes the implementation of inefficient projects, selected without any regard for their social rate of return."

[21] For example, the No.7 subway extension in New York City stretches 1 mile southwest from its previous terminus. This project was originally proposed in 2005, and construction started in 2007. The extension's opening was pushed back multiple times from its original target of December 2013. The extension finally opened to the public in September 2015. This project of building 1-mile subway takes 10 years.

for the ratio of low-skilled workers in each city in each year, and this helps solve the inter-city sorting problem. Regressing the ratio of low-skilled workers in each city on transit variables shows that transit variables have no significant effect on the proportion of less-educated individuals. Controlling for individual characteristics also mitigates this sorting issue. These individual controls are expected to be correlated with individual unobservables. Lastly, the results (Table A4) from an exogeneity test (Caetano, 2015) cannot reject the null that the transit variables are exogenous to the city-level LPF rates of low-skilled men. This test does not require the existence of instrumental variables and can only be applied in models with bunching points. As many cities do not have subway systems, I have many observations that are bunching at point 0 (0 subway miles).

In addition to the arguments above, I also have two sets of placebo tests that help verify the validity of the primary findings for low-skilled men who own no automobile. The first placebo test is studying the effect of public transit on the employment outcomes of highly educated workers. There are two reasons for the expectation that the labor supply decisions of workers with a college degree or above should not depend on public transit services. First, highly educated individuals can afford an automobile and rely less on public transit. The ratio of highly educated individuals who own private vehicles is 96 percent in 2014 while this number is only 82 percent for low-skilled workers. Second, highly educated individuals are more likely to have good job opportunities in labor markets because of better education. The second placebo test is conducting the same analysis for low-skilled men who have access to automobiles. These individuals benefit less from transit services and public transit services should have no or much smaller effect on their employment outcomes.

Public transit use is highly related to the private vehicle ownership variable v_j. Households who do not have private vehicles (no-vehicle group) have to rely on public transit, while households who own vehicles (vehicle group) rely less on public transit. To compare the effects of public transit for workers with and without a vehicle, it is interesting to run separate regressions for the vehicle group and the no-vehicle group. However, vehicle ownership is endogenous to work decisions because individuals in the labor force are more likely to afford vehicles. Failing to account for this endogeneity may bias the estimates of the coefficients of the transit variables. I use a reduced form OLS, 2SLS, and sample selection model to solve this problem.

4.1 Reduced form OLS

Suppose the vehicle ownership variable v_j is determined by the same covariates as LFP:

$$v_j = \alpha_0 + \alpha_1 S_{ct} + \alpha_2 B_{ct} + \alpha_3 R_{ct} + \alpha_4 X_j + \alpha_5 A_{ct} + \theta_c + \delta_t + \kappa_{jct} \tag{5}$$

Substitute the vehicle ownership equation into the labor supply equation:

$$\begin{aligned} E_{jct} = \beta_0 + \beta_5\alpha_0 + (\beta_1 + \beta_5\alpha_1)S_{ct} + (\beta_2 + \beta_5\alpha_2)B_{ct} + (\beta_3 + \beta_5\alpha_3)R_{ct} + \\ (\beta_4 + \beta_5\alpha_4)X_j + (\beta_6 + \beta_5\alpha_5)A_{ct} + (1 + \beta_5)\theta_c + (1 + \beta_5)\delta_t + \varepsilon_{jct} \\ + \kappa_{jct} \end{aligned} \tag{6}$$

This equation is a reduced form specification as v_j is substituted out. The reduced form estimate is a lower bound of β_1 if $\beta_5\alpha_1 < 0$, is an upper bound if $\beta_5\alpha_1 > 0$, and is consistent if $\beta_5\alpha_1 = 0$. If the individual characteristics (X_j) are driving the vehicle ownership decision and α_1 is close to zero, the reduced form OLS is likely to be consistent. For the sake of simplicity and interpretation, this model is estimated by simple OLS, although the estimates are robust to a logit model. [22]

4.2 2SLS and Heckman sample selection model

Equation (6) can be estimated by 2SLS with valid and strong instruments for v_j. Following Raphael and Rice (2002) and Baum (2009), state asset rules for welfare eligibility of Temporary Assistance for Needy Families (TANF), the state gasoline tax, and state auto insurance premiums are used as instruments for the vehicle ownership variable.[23] These instruments are valid because they are determined by states' political processes, gasoline tax regulation of each state, and the state-level auto insurance market, so the instruments are not correlated with individual labor market outcomes. Now equation (5) changes to

$$v_j = \alpha_0 + \alpha_1 S_{ct} + \alpha_2 B_{ct} + \alpha_3 R_{ct} + \alpha_4 X_j + \alpha_5 A_{ct} + \alpha_6 z_{st} + \theta_c + \delta_t + \kappa_{jct} \qquad (7)$$

z_{st} denotes the instruments. s represents state.

The state asset rules for eligibility of TANF refer to the maximum vehicle asset one can hold for being eligible of welfare. These rules vary across states and time. Following Sullivan (2006) and Baum (2009), I use two variables to characterize these rules. The first variable is a dummy indicating whether auto vehicles are included in the asset set determining welfare eligibility, and equals one if included, and zero otherwise. The second variable is the exempted

[22] To test the robustness of using simple OLS to model the binary LFP decision, a logit model is employed to estimate the impacts of transit on LFP. The regression results not shown here are very similar to the OLS results. The linear 2SLS estimation results (introduced in Section 3.2) are also robust to two logit regressions where the predicted residuals from the first stage are included in the second stage.

[23] Eligibility rules for welfare are from Urban Institutes Welfare Rules Database. State average insurance premium is from the Auto Insurance Database Report of National Association of Insurance Commissioners. Gasoline tax information is from the Brookings/Urban Institute's Tax Policy Center. The four state level instruments are linked to individual level data by year and state.

amount of vehicle value if auto vehicles are included in asset values when determining welfare eligibility. For example, one state may require that vehicle values cannot exceed \$5,000. In this case, the dummy variable equals one and the exempted amount variable equals \$5,000. These regulations may change over time. If, for example, the new rule is that vehicle assets do not affect eligibility, the dummy variable equals zero and the exempted amount equals zero.

The gasoline taxes and state-level insurance premiums influence vehicle ownership through the costs of maintaining and driving an automobile. Although the gasoline tax rate per gallon is small, the amount of tax paid can be large, especially for people who drive a lot. The insurance premium is a large monthly payment and can be a heavy burden for low-income individuals. For example, the average annual premium in New York State in 2013 is \$1301.

The summary statistics for these four instruments are displayed in table A5. It can be seen that there are sizeable changes in these four variables across time, and these temporal variations are used for identification in a fixed effect model.

An alternative specification to use the instruments is Heckman sample selection model (Heckman, 1979), which corrects the sample selection bias of estimating the effects of public transit for the vehicle group and the no-vehicle group. The first stage of the sample selection model is a probit model estimating equation (7). Heckman's inverse Mills ratio is included as a sample correction term in the second stage. The specification for the no-vehicle group is

$$E_{jct} = \beta_0 + \beta_1 S_{ct} + \beta_2 B_{ct} + \beta_3 R_{ct} + \beta_4 X_j + \beta_5 A_{ct} + \rho\sigma\lambda(\hat{v}_j) + \theta_c + \delta_t + \varepsilon_{jct} \qquad (8)$$

$\lambda(\hat{v}_j) = -\frac{\phi(\hat{v}_j)}{\Phi(\hat{v}_j)}$ is the inverse Mills ratio term. σ is standard deviation of ε_{jct}. ρ is correlation coefficient between ε_{jct} and κ_{jct}. For the vehicle group, the specification is the same except $\lambda(\hat{v}_j) = \frac{\phi(\hat{v}_j)}{\Phi(-\hat{v}_j)}$. [24]

5. Results

5.1 The effect of public transit on labor force participation

5.1.1 Reduced form OLS

Table 3 displays OLS regression results from the reduced form model (equation 6) for men with different levels of education. The dependent variable is equal to one if this individual is in labor force, and is zero otherwise. The full sample (all 161 cities), subway or rail cities, subway cities, and bus only cities are analyzed consecutively for robustness checks. [25]

Regression results reported in panel A are from the full sample. Subway services are found to increase the LFP of both low-skilled men and men with a high school degree or some college, although the effect for the former group is much larger than that of the latter group. The low-skilled men benefit more from subway services. Unsurprisingly, the coefficients of all public transit modes are small and insignificant for men with a college degree or above in all panels. This is consistent with the expectation that public transit availability is not a key factor in determining the LFP of highly educated workers. The regression results reported in column (3)

[24] Although the sample selection model assumes the distribution of error terms is jointly normal, the empirical results are not sensitive to this normal assumption. I follow Terza et al. (2008) and include the first stage predicted residuals instead of the inverse mills ratio term in the second stage regression. I also use a logit regression to model the second stage. The regression results not shown here are similar to the results obtained under the normal assumption.

[25] Subway or rail cities include cities that have subway or rail transit. Subway cities are those cities that have subway systems. Bus only cities contain cities that only have bus transit.

serve as a placebo test and help to confirm the correct specification of labor supply equation (equation 4).

Results for subway or rail cities in panel B are very similar, but the coefficient of subway miles per 1000 people is larger than the result in panel A. The service levels of rail transit start to increase the LFP of low-skilled men. The impact of subway miles is larger than the effect of rail miles. Subway services have the largest effect in subway cities (panel C). Panel D results for bus transit services show no statistically significant effect on LFP in bus only cities.

Results shown in Table 3 display evidence consistent with expectations, and support the specification of equation (4). The empirical findings also reveal statistically significant and positive impacts of better subway services on LFP. However, as noted above, the OLS estimates may be inconsistent if vehicle ownership is endogenous. To solve this endogeneity problem, the following analysis uses 2SLS and Heckman's sample selection model to identify the effects of transit on LFP.

5.1.2 2SLS and Heckman sample selection model

From here on, the analysis focuses on low-skilled workers as they benefit the most from public transit. Table 4 shows the regression results for the decision to own a private vehicle or not, which forms the first stages of 2SLS and Heckman's selection model. The dependent variable is binary with one indicating an individual living in a household that has one or more vehicles and zero indicating the household owning no automobile. The first stage for 2SLS is an OLS regression following equation (7), and the first stage for the sample selection model is a probit regression following equation (7). As all instruments are at the state level, standard errors are clustered at states.

For subway cities (column 3 and column 4), the first stages of the instrumental variables (IVs) are strong, with F statistics far larger than ten. The instruments pass the Sargan over-identification test, which further verifies they are valid. With the other covariates controlled, higher auto insurance premiums and gasoline taxes predict lower probabilities of owning an automobile. Tighter asset rules of welfare eligibility make workers less likely to have private vehicles for use.[26] The effects of instruments on vehicle ownership are consistent with the findings of Raphael and Rice (2002) and Baum (2009). The state auto insurance premium and gasoline tax are statistically significant in the probit model for subway or rail cities, although the F statistics for the OLS first-stage regression is less than ten. However, none of the instruments is significant for the full sample (all cities) and the bus only sample (bus only cities).

Two reasons may explain why these instruments are strong in subway cities but weak in bus only cities. First, compared with subway systems, bus transit is much slower in travel speed and is often not on time. It is very hard for low-skilled workers to travel long distances within short periods (e.g., 30 minutes) by bus. Thus, low-skilled individuals in bus only cities have to rely more on private vehicles and their vehicle ownership status is not sensitive to the instruments. Low-skilled workers in subway cities have much better travel alternatives (subway transit), so their vehicle ownership decisions are more sensitive to the instruments. The second possible reason is that the number of observations in each bus only city is small, as bus only cities are likely to have small city sizes. The smaller sample size for each bus only city may lead

[26] The welfare eligibility rule is tight under two cases. The first case is that one is not eligible for welfare if she owns a vehicle. Another situation is that one is not eligible if she owns a vehicle whose value exceeds a small number, e.g. $2000.

to weak power. Because of the weak instruments problems, one has to be careful in explaining the 2SLS and sample selection results for all cities and bus only cites. In these cases, I put more weight on the OLS results.

The results from the second stage regressions are reported in table 5. The dependent variable is binary with one indicating one is in labor force and zero otherwise. For ease of comparison, OLS regression results are also listed in table 5. The same models are estimated using observations from all cities, subway or rail cities, subway only cities, and bus only cities. For the sake of space, regression results for all cities and subway cities are shown in table 5, and estimates for subway or rail cities and bus only cities are displayed in the appendix (table A6).

Panel A in table 5 shows the regression results using the full sample (all cities). Results in column (1) control for the vehicle ownership variable explicitly. The significant coefficient of subway service is 0.429, which is very close to the result (0.437 in table 3) obtained in the reduced form OLS regression. Consistent with the existing literature, access to vehicles significantly improves tendency to work. Column (2) and column (3) display OLS regression results for the no-vehicle group and the vehicle group. Better bus and subway services significantly increase the LFP of low-skilled men without automobiles and have no significant effect on the LFP of low-skilled men who own automobiles. As already noted, the OLS results may have sample selection bias, as the vehicle ownership may be endogenous with the decision to work. To account for the bias, I use instrumental variables and column (4) shows the second stage results of 2SLS where the subway service variable remains statistically significant. In column (5) and column (6), I report results that use Heckman's sample selection model to account for sample selection bias. The results show that both bus and subway services significantly increase LFP. However, the 2SLS and Heckman selection model results here may suffer from weak instruments problems.

Regression results in panel B use individuals from subway cities. [27] The instruments are very strong for subway cities. The analysis for panel A holds qualitatively in panel B. The 2SLS and sample selection estimates are similar to the corresponding OLS results. The inverse Mills ratio terms are not significant, indicating that the sample selection bias is not present. Findings here support the view that public transit only improves LFP for workers who do not have private vehicles. This result rules out the uncontrolled common trends that might increase the LFP for both the vehicle group and the no-vehicle group.

The OLS coefficient of subway service variable in panel B is 0.655, which is similar to the 2SLS estimate (0.556) and the reduced form OLS result (0.695). This implies that the OLS estimates have small biases. The sample selection model for the no-vehicle group further confirms this. The coefficients of subway, bus, and rail service variables in the selection model are 3.770, 0.0369, and 0.0713, which are not significantly different from the OLS results where the corresponding coefficients are 3.910, 0.0366, and 0.119. The inverse Mills ratio term is small and not significant for the no-vehicle group, confirming the results from sample selection models are not significantly different from the OLS estimates. A simple Z test cannot reject the null that the estimates under OLS and sample selection models are the same.

The results in panel C (table A6) include individuals from subway or light rail cities. The analysis for Panel B holds here, except that rail systems now have a significant positive effect on

[27] On average, the regressions have 501 low-skilled men in a subway city in each year and 200 low-skilled men without automobiles in a subway city in each year.

tendency to work. No significant impact is found for bus transit in bus only cities (panel D in table A6).

The same series of regressions are conducted for men with a college degree or above. Results not shown here indicate that there is no significant impact of public transit on LFP in any specification, regardless of vehicle ownership. This finding is consistent with results in Table 3 and the expectation that transit has no effect on high-skilled workers' employment outcomes. This result rules out the uncontrolled common trends that might increase the LFP for both the low-skilled workers and the high-skilled workers.

The sample selection model for the no-vehicle group is my preferred specification because this model focuses on people who can benefit the most from transit and removes potential sample selection bias. The coefficient of subway service in subway cities is 3.77, which means LFP will increase by 377 percentage points if subway miles per 1000 people increase by one. The sample average of this subway measure in 2014 is 0.075 miles per 1000 people. Therefore, doubling the 2014 subway miles increases the LFP of low-skilled no-vehicle men by 28 percentage points ($3.77 \times 0.075 \times 100$) on average. Similarly, doubling the 2014 number of buses in subway and rail cities can increase tendency to work by 3.4 percentage points (from estimates in Panel B: $0.039 \times 0.87 \times 100$). Increasing the 2014 rail miles in subway and rail cities by 100 percent will increase probability of working by 3.0 percentage points (from estimates in panel C of table A5: $0.122 \times 0.24 \times 100$).

5.2 The effect of public transit on intensive margin outcomes

For people choosing to work, this subsection reports results on the effects of transit services on intensive margin outcomes, including work hours, hourly wages, and commuting times. Thus, the analysis only applies to employed low-skilled workers.

According to the theoretical model in section 2, the effects of public transit on work hours and commuting times depend on $w'(u)$. For minimum-wage earners ($w'(u) = 0$), better transit services increase hours of work and reduce commuting times. If the maximum wage one can receive is increasing in commuting distance ($w'(u) \geq 0$), the effect on work hours and commuting times is not determined. As the data do not contain the information on individual commuting distances, the relationship between wages and commuting distances is tested by evaluating the effect of transit systems on wages.

Table 6 shows the results of regressing hourly wages, work hours, and commuting times on transit services and other covariates. For brevity, I only display the results for subway cities. The regression results for the other cities are qualitatively similar.

The results in panel A indicate that there is weak evidence supporting that transit services improve wage rates for low-skilled workers in subway cities. [28] Columns (1) and (2) show that light rail services improve wages, but these results are not robust to the 2SLS and sample selection models. A possible explanation for this null finding is that many low-skilled men have part-time jobs and earn minimum wages. The minimum-wage earners have low-levels of human capital and they cannot find higher wages even if they commute longer distances. To test

[28] The dependent variable is hourly wage that is calculated by dividing annual wage income by hours worked per week and working weeks in a year. The hourly wage rate may suffer from measurement errors. People may report inaccurate information for hours worked per week. The information on number of work weeks in a year in ACS and Census is an interval variable. I choose the midpoint of the interval as the number of weeks. This may introduce measure errors, too. The measurement errors bias the estimate towards zero.

whether transit services enhance wages for full-time workers, I run similar regressions using low-skilled men who work 35 or more hours per week. I find a positive and statistically significant effect of subway service levels on wage rates in both the OLS and the sample selection models (see table A7).

A positive relationship between subway services and hourly wages indicates that faster transit speeds extend commuting distances ($\frac{du}{ds} > 0$) and wage rates are likely to increase in commuting distances ($\frac{dw}{du} > 0$). Under those circumstances, the theoretical model yields ambiguity about the effects of subway service levels on work hours and commuting times.

The results from all specifications in panel B show that transit services do not have statistically significant effects on work hours. Similar regressions are run for less-educated men who work 35 or more hours per week, and the results indicate no significant effect of transit services on hours worked per week.

The impacts of public transit on commuting times are shown in panel C. No significant effect exists. Therefore, the regression results support the conclusion that all three transit modes have no significant impact on commuting times. The analysis using less-educated men who work 35 or more hours per week shows similar patterns. Expanding the subway systems are likely to increase both commuting distances and commuting speeds, so the net effect on commuting times could be null.[29]

[29] The high-skilled men are analyzed by similar regressions, and I find no significant impact of transit on wage rates, hours worked per week, and commuting times.

5.3 Robustness checks

In addition to less-educated men, the same analysis is conducted for single women with less than a high school degree. For brevity and space, I only display results from the sample selection model for the vehicle group and the no-vehicle group in Table A8, although all other specifications (OLS, 2SLS) show similar results. The empirical results confirm that subway services improve tendency to work for low-skilled single women who do not have access to automobiles. On average, doubling the current subway miles increases the LFP of no-vehicle low-skilled single women by 32 percentage points, which is similar in magnitude to the effect for low-skilled men. The impacts on wage rates, hours worked per week, and commuting times are consistent with the findings for low-skilled men.[30]

The transit service variables used in previous analysis are in per capita terms. This raises the concern that some variations in these measures might come from the changes in city population. To test the robustness of the main results to different types of transit measures, I also conduct the same empirical analysis using the aggregate levels (e.g., subway miles, rail miles, and number of buses) to measure transit services in cities. The results in table A9 confirm that the significant effect of subway systems on LFP is robust to the aggregate measures.

The third robustness check is testing whether the empirical results are driven by an outlier city. Table A10 displays the regressions results for all subway cities except New York City. The estimated effects are similar to the results in panel B of table 5. I also try to exclude the other subway cities sequentially, and the regression results are qualitatively similar.

[30] Individuals with disabilities may also benefit from public transit services. Disabled people cannot drive and have to rely on public transit. However, the sample size of no-vehicle disabled people in my data is small. Another problem is that Census and ACS data does not have information on the degree of disabilities. Without information on the degree of disabilities, I cannot analyze the effects of public transit services on work for people with disabilities. The analysis for disabled people is left for future research.

6. Conclusions

Public transit is an important transportation option for low-skilled workers who cannot afford private vehicles. The average speed of subway system in New York City is about 15 miles per hour, which is much faster than the average speed (9 miles per hour) of driving in Manhattan.[31] Subway systems have the potential to help low-skilled workers search for jobs and commute to work.

This paper identifies the effects of subway systems on employment outcomes of low-skilled workers. For low-skilled men without automobiles, the empirical findings show that expanding subway systems by 10 percent increases their LFP by 3 percentage points. The impact of subway service is much larger than the effects of rail and bus systems. Subway access is found to increase wages, but has no significant effect on work hours and commuting times. All these findings imply that better subway services help low-skilled workers by increasing their travel speeds and extending the geographic scope of their labor market.

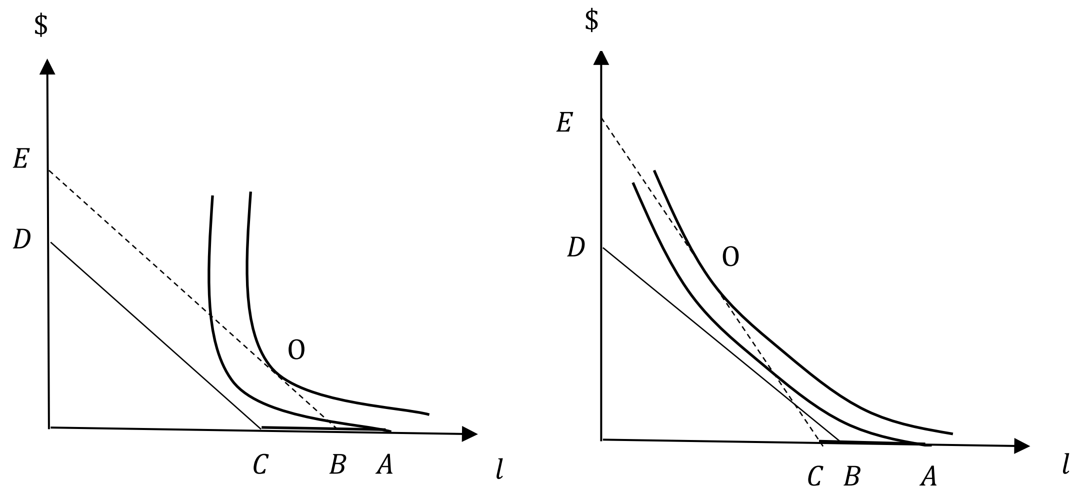
Accounting for the benefits identified in this paper is important in cost-benefit analysis of public transit programs. Although a comprehensive cost-benefit analysis is out the scope of this paper, a simple back-of-envelope analysis will still provide some estimates for the magnitudes of these benefits. For an average subway city with a subway network of 65 miles (130 directional route miles), the number of low-skilled individuals who own no automobile is about 96600. Increasing the subway miles by 10% will increase the LFP of no-vehicle low-skilled workers by 3 percentage points, which is 2898 workers. Assuming these workers earn an annual wage income of $12558 and an interest rate of 2.5%, the present value of these wage incomes for 20

[31] These speed numbers are from the following website pages:
http://www.nyctransitforums.com/forums/topic/17313-subway-system-average-speed-by-line/
http://www.wnyc.org/story/traffic-speeds-slow-nyc-wants-curb-car-service-growth/

years is 559 million. If the capital cost of building one-mile subway is set as $500 million, the benefits in wage incomes will account for 17% of the total capital costs.[32]

In addition to the low-skilled groups considered in this paper, any group of people who does not have access to private vehicles, because of low income or disability, can benefit from mass transit programs. Subway services not only help workers search for jobs and commute to work, it also makes people reach other places (e.g., restaurants and hospitals) more conveniently. What's more, the benefits of subway systems in reducing congestion and air pollution are not considered in the simple cost-benefit analysis above. The benefits identified in this paper are therefore lower bounds.

[32] The average subway city has a population of 1.5 million. I assume the subway systems are operating on both directions in a subway tunnel. Thus, the subway directional route miles are equal to the subway tunnel miles multiplied by two. The $12558 annual income is the average wage income of low-skilled no-vehicle workers in 2014. The capital costs of building one-mile subway range from $225 million per mile to $2.1 billion per mile. The ratio of benefits to costs will change if one varies the capital cost of building one-mile subway.



A: Given u, s increases   **B**: Given s, u increases

Figure 1: The effect of commuting speed on LFP

Table 1: Summary statistics for city transit services (1990, 2000, 2005-2014)

Transit measure	Mean	Cross section variation	Temporal variation	Inter-quartile range	Number of cities
Total measure:					
Total number of bus	306	517	75	247	153
Total subway miles	130	136	8	175	12
Total rail miles	273	308	83	427	31
Average measure:					
Number of bus per 1000 people	0.70	0.83	0.12	0.637	153
Subway miles per 1000 people	0.14	0.15	0.019	0.075	12
Rail miles per 1000 people	0.47	0.77	0.081	0.30	31

All the transit measures are calculated using the cities that have such transit modes. The bus transit measure is total number of bus or number of bus per 1000 people on day of maximum service. The rail measure is a summation of commuter rail, hybrid rail, and light rail.

Table 2: Labor market outcomes for different groups of individuals (2014)

Groups	LFP rate	Hours worked per week	Commuting time (minutes)	Hourly wage rate (dollars)
All people (men, women)	79%	39.9	30.4	27.6
People under poverty line	47%	31.5	30.4	11.3
Men with less than a high school degree	71%	39.4	32.6	16.3
Men with less than a high school degree, no vehicle	49%	38.0	40.4	15.3
Single women with less than a high school degree	52%	34.3	31.8	12.5
Single women with less than a high school degree, no vehicle	43%	33.6	39.5	12.2

[1] Calculation is for people between the ages of 25 and 60 from 2014 ACS. Hours worked per week, commuting time, and wage rate are summarized for employed people.
[2] The interquartile range for the city-level LFP of low-skilled men is 20%. The interquartile range for the city-level LFP of low-skilled men without automobiles is 32%.

Table 3: LFP (1 if in labor force; 0 if not) for men (reduced form OLS)

	(1)	(2)	(3)
VARIABLES	Men with less	Men with a high	Men with a
Panel A: All Cities			
Bus per 1000 people	0.0103	0.00422	-0.00124
	(0.0114)	(0.00680)	(0.00517)
Subway miles per 1000 people	0.437*	0.181***	0.0165
	(0.227)	(0.0528)	(0.0562)
Rail miles per 1000 people	0.0602	-0.000813	-0.00513
	(0.0385)	(0.0276)	(0.0132)
Year FE	12	12	12
City FE	161	161	161
Observations	169,087	619,531	403,616
R-squared	0.272	0.176	0.075
Panel B: Subway or Rail			
Bus per 1000 people	0.0129	0.0144	0.00172
	(0.0136)	(0.00861)	(0.00760)
Subway miles per 1000 people	0.523**	0.254***	0.0435
	(0.225)	(0.0536)	(0.0695)
Rail miles per 1000 people	0.0722**	0.00157	-0.000717
	(0.0303)	(0.0371)	(0.0177)
Year FE	12	12	12
City FE	36	36	36
Observations	100,088	329,420	250,640
R-squared	0.277	0.174	0.071
Panel C: Subway Cities			
Bus per 1000 people	0.0314	-0.00823	-0.0146
	(0.0217)	(0.00900)	(0.0106)
Subway miles per 1000 people	0.695***	0.244**	-0.0120
	(0.179)	(0.0924)	(0.0905)
Rail miles per 1000 people	0.162	0.0351	-0.0154
	(0.127)	(0.0485)	(0.0282)
Year FE	12	12	12
City FE	12	12	12
Observations	72,130	224,822	163,714
R-squared	0.278	0.170	0.072
Panel D: Bus Only Cities			
Bus per 1000 people	-0.0138	-0.00172	-0.00159
	(0.0216)	(0.0102)	(0.00572)
Subway miles per 1000 people	-	-	-
Rail miles per 1000 people	-	-	-
Year FE	12	12	12
City FE	138	138	138
Observations	68,999	290,111	152,976
R-squared	0.268	0.180	0.082

[1] Individual characteristics, interaction terms of individual characteristics, and city time-varying attributes are controlled but not displayed.

[2] Standard errors are clustered at city level (in parentheses). *** p<0.01, ** p<0.05, * p<0.1.

Table 4: First stage regression of vehicle ownership (1 if yes; 0 if no) for men with less than a high school degree

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All Cities		Subway Cities		Subway or Rail Cities		Bus Only Cities	
VARIABLES	OLS	Probit	OLS	Probit	OLS	Probit	OLS	Probit
State auto insurance premium	-2.21e-05	7.23e-06	-0.00028***	-0.00076***	-7.17e-05	-0.00032**	-1.60e-05	0.00019
	(6.64e-05)	(0.00017)	(5.14e-05)	(0.00015)	(7.00e-05)	(0.00015)	(9.73e-05)	(0.00024)
State gasoline tax	-0.00034	-0.0013	-0.0042***	-0.011***	-0.0019**	-0.0058**	0.00019	0.000427
	(0.00053)	(0.0017)	(0.00088)	(0.0030)	(0.00086)	(0.0024)	(0.00077)	(0.0032)
Vehicle is included in welfare eligibility rule	0.012	0.011	-0.166***	-0.466***	-0.0489	-0.123	0.014	0.046
	(0.020)	(0.076)	(0.040)	(0.152)	(0.0464)	(0.145)	(0.018)	(0.073)
Vehicle value excluded from welfare rule	-2.23e-06	-4.82e-06	1.38e-05**	3.97e-05**	3.87e-06	9.10e-06	-2.44e-06	-4.17e-06
	(1.75e-06)	(5.41e-06)	(4.67e-06)	(1.59e-05)	(3.94e-06)	(1.16e-05)	(1.72e-06)	(6.19e-06)
F statistics for IVs	2.65	-	69.26	-	2.74	-	0.63	-
p-value of over identification test	-	-	0.23	-	-	-	-	-
Year FE	12	12	12	12	12	12	12	12
City FE	159	159	12	12	36	36	128	128
Observations	169,087	169,072	72,130	72,130	100,088	100,088	68,999	68,984
R-squared	0.235	-	0.234	-	0.241	-	0.170	-

[1] Individual characteristics, interaction terms of individual characteristics, and city time-varying attributes are controlled but not displayed.

[2] Standard errors (in parenthesis) are clustered at State level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: LFP (1 if in labor force; 0 if not) for men with less than a high school degree

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS		**2SLS**	**Heckman Selection**	
VARIABLES	All	No	Vehicle	All	No	Vehicle
Panel A: All Cities						
Inverse Mill's Ratio	-	-	-	-	0.0978	-0.139***
	-	-	-	-	(0.076)	(0.0269)
Bus per 1000 people	0.0101	0.0483	-0.00188	0.00977	0.0497	-0.00365
	(0.0110)	(0.0219	(0.0105)	(0.0188)	(0.022)	(0.0107)
Subway miles per 1000	0.429**	1.812*	0.149	1.173**	1.676*	0.397
people	(0.199)	(0.692)	(0.331)	(0.564)	(0.716)	(0.320)
Rail miles per 1000	0.0586	0.101	0.0199	0.0550	0.0966	0.0203
people	(0.0397)	(0.0802	(0.0289)	(0.0430)	(0.0795	(0.0296)
At least one vehicle present	0.187**	-	-	-0.636	-	-
	(0.0210)	-	-	(0.446)	-	-
F statistics for IVs	-	-	-	2.65	-	-
Year FE	1 2	12	12	12	12	12
City FE	159	159	159	159	159	159
Observations	169,087	49,175	119,897	169,087	49,175	119,897
R-squared	0.299	0.306	0.214	0.263	0.306	0.214
Panel B: Subway Cities						
Inverse Mill's Ratio	-	-	-	-	0.115	0.0371
	-	-	-	-	(0.104)	(0.0578)
Bus per 1000 people	0.0273	0.0366	0.0466*	0.0204	0.0369	0.0436
	(0.0204)	(0.0066	(0.0252)	(0.0142)	(0.0068	(0.0244)
Subway miles per 1000	0.655**	3.910*	0.123	0.556*	3.770*	0.0770
people	(0.170)	(1.054)	(0.324)	(0.332)	(1.047)	(0.311)
Rail miles per 1000	0.116	0.119	0.188	0.0368	0.0713	0.169
people	(0.121)	(0.125)	(0.110)	(0.120)	(0.111)	(0.108)
At least one vehicle present	0.138**	-	-	0.418**	-	-
	(0.0169)	-	-	(0.190)	-	-
F statistics for IV	-	-	-	69.26	-	-
p-value of over	-	-	-	0.23	-	-
Year FE	12	12	12	12	12	12
City FE	12	12	12	12	12	12
Observations	72,130	28,660	43,470	72,130	28,660	43,470
R-squared	0.295	0.311	0.199	0.221	0.311	0.199

[1] Individual characteristics, interaction terms of individual characteristics, and city time-varying attributes are controlled but not displayed.

[2] Standard errors (in parenthesis) are clustered at city level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Intensive margins for men with less than a high school degree (subway cities)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		OLS			**2SLS**	**Heckman**	
VARIABLES	All	All	No	Vehicle	All	No	Vehicle
Panel A: Hourly wages							
Inverse Mill's Ratio	-	-	-	-	-	0.464	0.806
	-	-	-	-	-	(0.841)	(0.633)
Bus per 1000 people	0.838	0.861	1.221	0.604	0.703*	1.284	0.524
	(0.561)	(0.512)	(0.839)	(0.566)	(0.381)	(0.855)	(0.550)
Subway miles per	5.310	5.311	5.900	4.182	-0.491	4.532	4.525
1000 people	(3.442)	(3.544)	(7.037)	(3.575)	(2.792)	(7.642)	(4.616)
Rail miles per	2.645*	2.017*	0.338	2.188	0.249	0.357	1.371
1000 people	(1.035)	(0.994)	(1.975)	(1.324)	(1.599)	(1.983)	(1.478)
At least one vehicle	-	1.979*	-	-	8.026**	-	-
present	-	(0.151)	-	-	(2.653)	-	-
Observations	48,217	48,217	15,688	32,529	47,444	15,688	32,529
R-squared	0.147	0.160	0.108	0.153	0.035	0.108	0.153
Panel B: Work hours							
Inverse Mill's Ratio	-	-	-	-	-	-	3.042**
	-	-	-	-	-	(0.792)	(1.133)
Bus per 1000 people	-0.386	-0.414	-2.552	1.167	-0.785	-2.182	1.112
	(2.561)	(2.511)	(4.100)	(1.747)	(1.715)	(4.249)	(1.582)
Subway miles per	-5.584	-5.764	-17.28	-2.059	-8.191	-14.45	0.702
1000 people	(9.752)	(9.820)	(19.93)	(10.44)	(10.66)	(19.74)	(9.808)
Rail miles per	-1.600	-1.815	5.399	-3.438	1.062	6.899	-1.125
1000 people	(1.637)	(1.542)	(5.816)	(2.213)	(0.846)	(6.445)	(1.197)
At least one vehicle	-	0.600*	-	-	10.2***	-	-
present	-	(0.217)	-	-	(2.720)	-	-
Observations	64,802	64,802	18,206	46,596	64,029	18,206	46,596
R-squared	0.147	0.162	0.111	0.155	0.058	0.111	0.155
Panel C: Commuting times							
Inverse Mill's Ratio	-	-	-	-	-	6.595*	2.733*
	-	-	-	-	-	(3.218)	(1.457)
Bus per 1000 people	-1.561	-1.870	-0.485	-0.325	-0.268	-0.0797	-0.328
	(1.671)	(1.682)	(4.480)	(1.549)	(2.499)	(4.369)	(1.671)
Subway miles per	-10.51	-14.13	-48.15	0.351	0.00400	-38.38	8.649
1000 people	(13.15)	(14.03)	(69.44)	(11.65)	(18.69)	(69.36)	(12.26)
Rail miles per	-6.211	-5.168	7.451	-7.389	0.234	5.962	-8.001
1000 people	(5.109)	(5.138)	(9.270)	(6.643)	(2.047)	(8.997)	(6.798)
At least one vehicle	-	-	-	-	10.95	-	-
present	-	(1.240)	-	-	(12.90)	-	-
Observations	43,190	43,190	13,045	30,145	43,190	13,045	30,145
R-squared	0.049	0.056	0.033	0.047	0.026	0.033	0.047

[1] People who have positive wages and work hours are included in panel A. People who have positive work hours or commuting times are included in panel B and C, respectively.
[2] Individual characteristics, interaction terms of individual characteristics, city time-varying attributes, industry fixed effects, occupational earning score, 12 city fixed effects, and 12 year fixed effects are controlled but not displayed.
[3] Standard errors (in parenthesis) are clustered at city level. *** p<0.01, ** p<0.05, * p<0.1. The first stage F statistics for the 2SLS regressions are 17.8, 74.2, and 29.5, respectively. All 2SLS regressions pass the over-identification test.

Appendix

1. Theoretical derivation of $\frac{dh}{ds}$ and $\frac{du}{ds}$.

This section derives the effect of commuting speeds on hours worked ($\frac{dh}{ds}$) and the effect of commuting speeds on commuting distance ($\frac{du}{ds}$) when the maximum wage rate $w(u)$ that the agent receives is increasing in commuting distance u ($w'(u) \geq 0,\ w''(u) \leq 0$).

The agent varies h and u to maximize utility:

$$\max_{h,u} U(T - h - \frac{u}{s}, w(u)h)$$

The F.O.C.s are:

$$\frac{\partial U}{\partial h} = -U_1 + U_2 w(u) = 0$$

$$\frac{\partial U}{\partial u} = -U_1/s + U_2 h w'(u) = 0$$

The S.O.C.s are $\frac{\partial^2 U}{\partial h^2} < 0, \frac{\partial^2 U}{\partial u^2} < 0,\ \frac{\partial^2 U}{\partial h^2}\frac{\partial^2 U}{\partial u^2} > (\frac{\partial^2 U}{\partial h \partial u})^2$. Solve the total derivatives with respect to u, h, and s for the F.O.C.s:

$$\frac{\partial^2 U}{\partial h \partial u} du + \frac{\partial^2 U}{\partial h^2} dh + \frac{\partial^2 U}{\partial h \partial s} ds = 0$$

$$\frac{\partial^2 U}{\partial u^2} du + \frac{\partial^2 U}{\partial h \partial u} dh + \frac{\partial^2 U}{\partial u \partial s} ds = 0$$

where $\frac{\partial^2 U}{\partial h \partial s} > 0, \frac{\partial^2 U}{\partial u \partial s} > 0$, and

$$\frac{\partial^2 U}{\partial h \partial u} = \underbrace{\frac{U_{11}}{s} - \frac{w(u)U_{21}}{s}}_{(-)} + w'(u)[\underbrace{U_2}_{Substitution\ effect\ (+)} + \underbrace{hw(u)U_{22} - hU_{12}}_{Income\ effect\ (-)}] \lesseqgtr 0$$

Solve $\frac{dh}{ds}$:

$$\frac{dh}{ds} = \frac{\frac{\partial^2 U}{\partial h \partial u}\frac{\partial^2 U}{\partial u \partial s} - \frac{\partial^2 U}{\partial u^2}\frac{\partial^2 U}{\partial h \partial s}}{\frac{\partial^2 U}{\partial h^2}\frac{\partial^2 U}{\partial u^2} - (\frac{\partial^2 U}{\partial h \partial u})^2} = \frac{\frac{\partial^2 U}{\partial h \partial u} * positive + positive}{positive}$$

Table A1: Residence status for people who live in MSAs

Central city residence status	People with less than a high school degree (%)	People with a high school or some college degree (%)	People with a college degree or above (%)
Central city/principle city	26.6	16.8	18.3
Outside central/principle city	33.4	40.8	42.4
Principal city status unknown	40.1	42.4	39.3

The results are for people between the ages of 25 and 60. 1990, 2000 Census, and 2005-2014 ACS are used for calculation.

Table A2: Simple correlation between transit services and city socioeconomic status in 2000

City socioeconomic status	Length of subway systems	Length of rail systems	Number of buses
Proportion of low-skilled individuals	0.040	0.092	0.040
Labor force participation rate	-0.16	-0.27	-0.25

The results are simple correlation coefficients between city-level transit services and city-level socioeconomic variables. The city-level socioeconomic status variables are aggregated from Census 2000 data.

Table A3: The length of subway systems from 1990 to 2014 (in miles)

City	1990	2000	2005	2007	2009	2011	2014
Los Angeles, CA	0	31.9	31.9	31.9	31.9	31.9	31.9
San Francisco, CA	142	190.1	209	209	209	209	209
Washington, DC	156.2	193.5	211.8	211.8	211.8	211.8	211.8
Chicago, IL	191	206.3	206.3	207.8	207.8	207.8	207.8
Atlanta, GA	67.0	92.1	96.1	96.1	96.1	96.1	96.1
Baltimore, MD	26.6	29.4	29.4	29.4	29.4	29.4	29.4
Miami, FL	42.2	42.2	45	45	45	45	45.8
New York, NY	492.9	492.9	493.8	493.8	493.8	487.5	487.5
Philadelphia, PA	75.8	76.1	74.9	74.9	74.9	74.9	74.9
Boston, MA	76.7	76.3	76.3	76.3	76.3	76.3	76.3
Cleveland, OH	38.2	38.2	38.1	38.1	38.1	38.1	38.1
Jersey City, NJ	28.6	28.6	28.6	28.6	28.6	28.6	28.6

Table A4: Exogeneity test for transit variables

Variables	Bandwidth (percentile of range)			
	5%	10%	20%	50%
A: 84 cities with populations larger than 0.2 million (634 city-year observations)				
Subway miles per 1000 people	-2.49	0.030	0.016	-0.038
	(2.34)	(0.039)	(0.037)	(0.029)
Rail miles per 1000 people	-0.103	-0.017	0.013	-0.059***
	(0.090)	(0.041)	(0.030)	(0.019)
Bus per 1000 people	-0.39***	-0.43***	-0.47***	-0.46***
	(0.077)	(0.066)	(0.045)	(0.025)
B: 55 cities with populations larger than 0.3 million (450 city-year observations)				
Subway miles per 1000 people	-2.10	0.021	0.020	0.00024
	(1.45)	(0.024)	(0.023)	(0.018)
Rail miles per 1000 people	-0.054	-0.092	-0.0031	0.18***
	(0.13)	(0.059)	(0.043)	(0.027)
Bus per 1000 people	0.90	0.58	0.56	0.34
	(2.33)	(2.04)	(1.30)	(0.74)

[1] The tests are calculated using method of Caetano (2015). Table shows the test statistics and standard errors (in parenthesis) for three transit variables.

[2] I calculate average LFP of low-skilled men for each city in each year. Then apply the city-year level data to the test statistics.

[3] The 5%, 10%, 20%, and 50% percentiles are chosen as bandwidths for conducting the test, respectively.

[4] The null hypothesis is that the transit variables are exogenous after controlling for all the covariates. In most cases, the null hypothesis cannot be rejected.

[5] For cities with population smaller than 0.3 million, the number of observations in each city is smaller. This may lead to inaccurate measures of LFP and rejection of null for bus in Panel A. For the same reason, I exclude cities with populations smaller than 0.2 million from the test. All subway and rail cities are included in the test.

[6] For cities that only have bus transit, subway miles per 1000 people and rail miles per 1000 people are set to zero. This leads to bunching points that are necessary for the test.

[7] Individual characteristics, interaction terms of individual characteristics, city time-varying attributes, city fixed effects, and year fixed effects are controlled but not displayed.

Table A5: Summary statistics for the instrumental variables

Instrumental variables	Mean	Cross section variation	Temporal variation	Number of states
State auto insurance premium (dollars)	896	177	62	42
State gasoline tax (cents per gallon)	21	5.2	2.4	42
Vehicle is included in welfare liability rule (=1 if yes, =0 if no)	0.45	0.44	0.25	42
Vehicle value excluded from welfare eligibility rule (dollars)	2616	3263	1593	42

Table A6: LFP (1 if in labor force; 0 if not) for men with less than a high school degree

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS		**2SLS**	**Heckman**	
VARIABLES	All	No	Vehicle	All	No	Vehicle
Panel C: Subway or Rail Cities						
Inverse Mill's Ratio	-	-	-	-	0.0971	-0.0193
	-	-	-	-	(0.0865)	(0.0301)
Bus per 1000 people	0.0109	0.0422**	0.0003	0.0126	0.0392*	0.00112
	(0.0124)	(0.0178)	(0.0158	(0.0146)	(0.0174)	(0.0159)
Subway miles per 1000	0.501**	2.932***	-0.0460	0.674**	2.772**	-
people	(0.206)	(0.479)	(0.345)	(0.279)	(0.481)	(0.338)
Rail miles per 1000	0.0667**	0.127**	0.0007	0.0648***	0.122**	0.00129
people	(0.0319)	(0.0504)	(0.0314	(0.0245)	(0.0505)	(0.0314)
At least one vehicle	0.156***	-	-	0.0929	-	-
present	(0.0195)	-	-	(0.295)	-	-
F statistics for IVs	-	-	-	2.74	-	-
Year FE	12	12	12	12	12	12
City FE	36	36	36	36	36	36
Observations	100,088	35,263	64,825	100,088	35,263	64,825
R-squared	0.298	0.312	0.202	0.293	0.312	0.202
Panel D: Bus Only Cities						
Inverse Mill's Ratio	-	-	-	-	-	-
	-	-	-	-	(0.107)	(0.0913)
Bus per 1000 people	-0.0116	-0.0197	-0.0160	-0.0316	-0.0375	-0.0300
	(0.0196)	(0.0493)	(0.0187	(0.0513)	(0.0486)	(0.0198)
Subway miles per 1000	-	-	-	-	-	-
people	-	-	-	-	-	-
Rail miles per 1000	-	-	-	-	-	-
people	-	-	-	-	-	-
At least one vehicle	0.248***	-	-	-1.649	-	-
present	(0.0121)	-	-	(2.486)	-	-
F statistics for IVs	-	-	-	0.63	-	-
Year FE	12	12	12	12	12	12
City FE	128	128	128	128	128	128
Observations	68,999	13,912	55,072	68,999	13,912	55,072
R-squared	0.307	0.253	0.227	0.201	0.255	0.227

[1] Individual characteristics, interaction terms of individual characteristics, and city time-varying attributes are controlled but not displayed.

[2] Standard errors (in parenthesis) are clustered at city level. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: hourly wage for men with less than a high school degree who work 35 hours or more per week (subway cities)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		OLS			**2SLS**	**Heckman Selection**	
VARIABLES	All	All	No vehicle	Vehicle	All	No vehicle	Vehicle
Inverse Mill's Ratio	-	-	-	-	-	0.680	1.002
	-	-	-	-	-	(0.636)	(0.632)
Bus per 1000 people	0.690	0.721*	0.877	0.563	0.711*	1.016	0.425
	(0.409)	(0.395)	(0.707)	(0.446)	(0.421)	(0.648)	(0.435)
Subway miles per	10.60	10.62	18.26*	4.410	-48.87	16.78*	9.120
1000 people	(9.920)	(9.914)	(9.724)	(11.46)	(35.42)	(9.556)	(15.23)
Rail miles per 1000	1.529	1.222	0.0315	1.249	0.753	0.707	0.723
people	(1.272)	(1.283)	(2.956)	(1.438)	(1.600)	(0.706)	(1.613)
At least one vehicle	-	1.902***	-	-	6.433***	-	-
present	-	(0.151)	-	-	(2.020)	-	-
Observations	39,460	39,460	12,532	26,928	39,460	12,532	26,928
R-squared	0.175	0.187	0.134	0.178	0.134	0.134	0.178

[1] Only people who have positive wages and work 35 hours or more per week are included in regression.
[2] Individual characteristics, interaction terms of individual characteristics, city time-varying attributes, industry fixed effects, occupational earning score, 12 city fixed effects, and 12 year fixed effects are controlled but not displayed
[3] Standard errors (in parenthesis) are clustered at city level. *** p<0.01, ** p<0.05, * p<0.1. The first-stage F statistics for the 2SLS regression is 26.2. The IVs pass the over-identification test.

Table A8:Robustness check: single women with less than a high school degree
(sample selection model results, subway cities)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LFP		Hourly wage		Hours worked		Commuting time	
VARIABLES	No vehicle	Vehicle	No vehicle	Vehicle	No vehicle	Vehicle	No vehicle	Vehicle
Inverse Mill's Ratio	-0.00149	0.218***	-1.872	-1.891*	-3.191	2.419	8.373	-10.22*
	(0.0896)	(0.0414)	(1.445)	(1.044)	(2.576)	(2.182)	(11.53)	(4.732)
Bus per 1000 people	0.00330	0.157	0.0763	0.907	4.175*	0.484	-22.49**	17.28**
	(0.0673)	(0.0865)	(0.977)	(0.636)	(1.922)	(1.382)	(9.220)	(6.213)
Subway miles per 1000 people	4.290***	1.726	16.35	5.600	-8.914	35.00	-108.8	494.1
	(0.406)	(1.180)	(14.04)	(8.462)	(40.30)	(25.44)	(486.6)	(280.6)
Rail miles per 1000 people	0.275	-0.0752	1.859	2.480	-0.233	8.577	-16.71	-10.23
	(0.160)	(0.0572)	(3.064)	(2.661)	(5.848)	(7.425)	(10.92)	(15.39)
Year FE	12	12	12	12	12	12	12	12
City FE	12	12	12	12	12	12	12	12
Industry FE	-	-	32	32	32	32	32	32
Observations	21,143	15,206	8,539	8,682	9,000	9,247	6,829	7,564
R-squared	0.152	0.123	0.108	0.135	0.051	0.054	0.051	0.077

[1] Only people who are employed are included in regression for columns 3-8.
[2] Individual characteristics, interaction terms of individual characteristics, and city time-varying attributes are controlled but not displayed.
[3] Industry fixed effects are included in columns 3-8. Occupation earnings score is included in columns 3-4.
[4] Standard errors (in parenthesis) are clustered at city level. *** p<0.01, ** p<0.05, * p<0.1.

Table A9:Robustness check: LFP (1 if in labor force; 0 if not) for men with less than a high school degree (using aggregate transit service levels, subway cities)

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS		**2SLS**	**Heckman Selection**	
VARIABLES	All	No vehicle	Vehicle	All	No vehicle	Vehicle
Inverse Mill's Ratio	-	-	-	-	0.0979	0.0515
	-	-	-	-	(0.0948)	(0.0622)
log(number of bus)	0.0404	0.0348	0.0516	0.0373	0.0351	0.0467
	(0.0267)	(0.0229)	(0.0409)	(0.0238)	(0.0245)	(0.0396)
log(subway miles)	0.250**	0.948***	0.0173	0.210*	0.875***	-0.00758
	(0.113)	(0.107)	(0.0970)	(0.110)	(0.117)	(0.0877)
log(rail miles)	-0.000852	-0.00835	0.00578	0.000739	-0.00636	0.00680
	(0.00523)	(0.00499)	(0.00403)	(0.00438)	(0.00591)	(0.00463)
At least one vehicle present	0.138***	-	-	0.455***	-	-
	(0.0169)	-	-	(0.171)	-	-
F statistics for IV	-	-	-	13.75	-	-
p-value of over identification test	-	-	-	0.19	-	-
Year FE	12	12	12	12	12	12
City FE	12	12	12	12	12	12
Observations	72,130	28,660	43,470	72,130	28,660	43,470
R-squared	0.295	0.311	0.199	0.201	0.311	0.199

[1] Individual characteristics, interaction terms of individual characteristics, and city time-varying attributes are controlled but not displayed.
[2] Standard errors (in parenthesis) are clustered at city level. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Robustness check: LFP (1 if in labor force; 0 if not) for men with less than a high school degree (excluding New York City, subway cities)

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS		**2SLS**	**Heckman Selection**	
VARIABLES	All	No vehicle	Vehicle	All	No vehicle	Vehicle
Inverse Mill's Ratio	-	-	-	-	-0.344	0.269**
	-	-	-	-	(0.211)	(0.0942)
Bus per 1000 people	0.0320	0.0206	0.0477	0.0116	0.0408	0.0242
	(0.0286)	(0.0254)	(0.0372)	(0.0349)	(0.0377)	(0.0332)
Subway miles per	0.597**	3.736***	0.122	0.647**	3.881***	0.0156
1000 people	(0.196)	(0.982)	(0.334)	(0.304)	(0.977)	(0.294)
Rail miles per 1000	0.131	0.0589	0.151	0.0172	0.150	0.0856
people	(0.127)	(0.138)	(0.108)	(0.106)	(0.197)	(0.0900)
At least one vehicle	0.162***	-	-	0.598***	-	-
present	(0.0189)	-	-	(0.215)	-	-
F statistics for IV	-	-	-	12.19	-	-
p-value of over identification test	-	-	-	0.34	-	-
Year FE	12	12	12	12	12	12
City FE	11	11	11	11	11	11
Observations	44,712	12,254	32,458	44,712	12,254	32,458
R-squared	0.313	0.317	0.214	0.152	0.317	0.215

[1] Individual characteristics, interaction terms of individual characteristics, and city time-varying attributes are controlled but not displayed.

[2] Standard errors (in parenthesis) are clustered at city level. *** p<0.01, ** p<0.05, * p<0.1.

References

Anderson, M. L. (2014). Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion. *American Economic Review, 104*(9), 2763-96.

APTA. (2014). 2014 Public transportation fact book. American Public Transportation Association, Washington, DC.

APTA. (2015). Public transportation investment background data. Technical report, American Public Transportation Association, Washington, DC.

Bartik, T. J. (1992). Who benefits from state and local economic development policies. *Journal of the American Planning Association*, 58.2, 258–259.

Baum, C. L. (2009). The effects of vehicle ownership on employment. Journal of Urban Economics, 66(3), 151-163.

Baum-Snow, N., & Kahn, M. E. (2000). The effects of new public projects to expand urban rail transit. *Journal of Public Economics*, *77*(2), 241-263.

Berechman, J. (2010). *The evaluation of transportation investment projects*. Routledge.

Blumenberg, E., & Ong, P. (1998). Job accessibility and welfare usage: Evidence from Los Angeles. *Journal of Policy Analysis and Management*, 639-657.

Brueckner, J. K., & Rosenthal, S. S. (2009). Gentrification and neighborhood housing cycles: will America's future downtowns be rich?. *The Review of Economics and Statistics, 91*(4), 725-743.

Caetano, C. (2015). A test of exogeneity without instrumental variables in models with bunching. *Econometrica*, *83*(4), 1581-1600.

DOT. (2011). Highway statistics 2010. Technical report, US Department of Transportation, Washington, DC.

Duranton, G., & Turner, M. A. (2011). The fundamental law of road congestion: Evidence from US cities. *American Economic Review, 101*(6), 2616-52.

Gendron-Carrier, N., Gonzalez-Navarro, M., Polloni, S., & Turner, M. A. (2018). *Subways and urban air pollution* (No. w24183). National Bureau of Economic Research.

Glaeser, E. L., Kahn, M. E., & Rappaport, J. (2008). Why do the poor live in cities? The role of public transportation. *Journal of urban Economics*, *63*(1), 1-24.

Gobillon, L., Selod, H., & Zenou, Y. (2007). The mechanisms of spatial mismatch. *Urban studies, 44*(12), 2401-2427.

Gonzalez-Navarro, M., & Turner, M. A. (2016). Subways and urban growth: evidence from earth.

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, *47*(1), 153-161.

Hellerstein, J. K., Kutzbach, M. J., & Neumark, D. (2014). Do labor market networks have an important spatial dimension?. *Journal of Urban Economics*, *79*, 39-58.

Holzer, H. J., Quigley, J. M., & Raphael, S. (2003). Public transit and the spatial distribution of minority employment: Evidence from a natural experiment. *Journal of Policy Analysis and Management*, *22*(3), 415-441.

Holzer, H. J., Ihlanfeldt, K. R., & Sjoquist, D. L. (1994). Work, search, and travel among white and black youth. *Journal of Urban Economics*, *35*(3), 320-345.

Ihlanfeldt, K. R., & Sjoquist, D. L. (1989). The impact of job decentralization on the economic welfare of central city blacks. *Journal of Urban Economics*, *26*(1), 110-130.

Kain, J. F. (1968). Housing segregation, negro employment, and metropolitan decentralization. *The Quarterly Journal of Economics*, *82*(2), 175-197.

Litman, T. (2007). Evaluating rail transit benefits: A comment. *Transport Policy*, *14*(1), 94-97.

Litman, T. (2015). *Evaluating public transit benefits and costs*. British Columbia, Canada: Victoria Transport Policy Institute.

Ong, P. M. (2002). Car ownership and welfare-to-work. *Journal of Policy Analysis and Management*, *21*(2), 239-252.

Parry, I. W., & Small, K. A. (2009). Should urban transit subsidies be reduced?. *American Economic Review*, *99*(3), 700-724.

Rosenbaum, J. E. (1995). Changing the geography of opportunity by expanding residential choice: Lessons from the Gautreaux program. *Housing Policy Debate*, *6*(1), 231-269.

Raphael, S., & Rice, L. (2002). Car ownership, employment, and earnings. *Journal of Urban Economics*, *52*(1), 109-130.

Ruggles, S., Genadek, K., Goeken R., Grover J., and Sobek M. (2015). Integrated Public Use Microdata Series: Version 6.0 [dataset]. Minneapolis: University of Minnesota.

Sanchez, T. W. (1999). The connection between public transit and employment: the cases of Portland and Atlanta. *Journal of the American Planning Association*, *65*(3), 284-296.

Schuetz, J., Larrimore, J., Merry, E. A., Robles, B. J., Tranfaglia, A., & Gonzalez, A. (2017). Are central cities poor and non-white?. *Journal of Housing Economics*.

Sullivan, J. X. (2006). Welfare reform, saving, and vehicle ownership do asset limits and vehicle exemptions matter?. *Journal of human resources, 41*(1), 72-105.

Terza, J. V., Basu, A., & Rathouz, P. J. (2008). Two-stage residual inclusion estimation: addressing endogeneity in health econometric modeling. *Journal of health economics*, *27*(3), 531-543.

Winston, C., & Maheshri, V. (2007). On the social desirability of urban rail transit systems. *Journal of urban economics*, *62*(2), 362-382.

Chapter 3: Do Subways Reduce Congestion? Evidence from US Cities

Jindong Pang
Department of Economics
Syracuse University

1. Introduction

Congestion on urban road systems has been rising in U.S. cities in recent years. The annual delay from congestion on urban road systems cost commuters in 471 urban areas in 2014 roughly 42 hours, about the equivalent of one week of work. That was up sharply from 1982 for which the corresponding estimate was just 18 hours.[33] Congestion is also much worse in large cities. The annual delay per auto commuter for the 15 largest urban areas in 2014 amounted to 63 hours.

Given the extensive cost associated with urban congestion, not surprisingly, congestion has been the focus of numerous studies as well as policy initiatives intended to alleviate congestion. One policy response has been to "build your way out of congestion" by expanding road systems. However, this approach is not effective to reduce congestion because people respond to expansions to the road network by traveling more miles.[34] Duranton and Turner (2011) find the elasticity of highway traffic with respect to highway capacity is 1.03, confirming the fundamental law of road congestion. This law, which Downs (1962) proposed 55 years ago, states that traffic increases one for one with roads and building more roads will not reduce congestion. Hsu and Zhang (2014) show that this law holds for highways in Japan.

Public transit is another proposed method to alleviate road congestion. The American Public Transit Association claims "Without public transportation, congestion would have increased by 27 percent".[35] Several studies (Nelson et al., 2007; Parry and Small, 2009; Anderson, 2014) find subway and light rail systems reduce travel times on roads in Los Angeles and Washington, DC. Duranton and Turner (2011) find alternative evidence showing that the

[33] The congestion cost estimates in this paragraph are from a report by Texas A&M Transportation Institutes (David et al., 2015).
[34] See Goodwin (1996) and Cervero (2002) for reviews.
[35] http://www.apta.com/resources/reportsandpublications/documents/congestion.pdf

effect of bus transit on highway usage is not significant. They conclude the transit system does not help reduce congestion on roads. Thus, the current literature has not reached consensus on the role of public transit in congestion relief.

This paper investigates the role of subway systems in congestion relief by studying the effects of subway expansions on passenger miles traveled (PMT) in subways and vehicle miles traveled (VMT) on roads in the US. Conceptually, adding more subways can affect traffic in three ways. First, increasing access will generate higher usage and ridership of subway systems. Second, better subway services may motivate some passengers to substitute from other modes, e.g., driving. Third, subway systems may change the distribution of economic activities and decentralize cities (Gonzalez-Navarro and Turner, 2016).[36] A more dispersed city configuration leads to longer trips. All three impacts boost subway ridership. The second channel reduces traffic on roads while the third effect may cause more congestion on roads.

The empirical results reported in this paper indicate that the elasticity of subway PMT with respect to subway miles is 1.27, implying that the fundamental law of road congestion applies to subway systems. Subway expansions also have substitution and growth effects on road traffic. A 10 percent expansion of subway systems reduces contemporaneous traffic on ring highways and non-highway arterial roads by 0.7 percent and 1.4 percent, respectively. With a three-year lag, a 10 percent increase in subway capacity increases VMT on ring highways by 0.4 percent and increase VMT on radial highways by 1.7 percent. The reason for the growth effects might be that subway systems decentralize cities. Taking both the substitution and growth effects into consideration, building more subways does not mitigate congestion in subways and

[36] The effect of subways here are similar to highways. Baum-Snow (2007) finds that highways decentralize cities.

congestion on radial highways, but relieves congestion on ring highways and non-highway arterial roads.

This study contributes to current literature in several ways. To the author's knowledge, this is the first paper that confirms the fundamental law of road congestion applies to subway systems. Given a fixed number of passengers, the comfort level in subway stations and subway cars increases after subway expansions. The higher comfort level will attract more riders from other travelling modes. A conceptual model shows that in equilibrium, the comfort level should be the same as the comfort level before the expansions of subway systems. This means subway PMT should increase at least the same percentages as subway miles. Robustness checks show that this law also applies to light rail and bus systems. The existence of fundamental law of public transit congestion indicates that providing more transit services will not mitigate congestion in public transit. This law also helps predict ridership changes after adding more public transit services.

Second, this paper reconciles the inconsistent evidence about effects of transit on road congestion. Notably, subway expansions only reduce congestion on roads that are close substitutes to subways. For example, non-highway arterial roads have lower speed limits and usually serve local urban neighborhoods, so they share similar traits with subways in travel speeds and geographic coverages. The empirical results suggest subway expansions relieves congestion and have the largest effects on VMT on non-highway arterial roads. In that respect, the empirical findings support the positive role of subway systems in reducing congestion.

A third and a new contribution of this paper is the growth effects that added subways have on VMT on interstate highways, especially for radial highways. This positive effect of subway systems on highway traffic echoes Gonzalez-Navarro and Turner's (2016) finding that subway expansions decentralize cities. Subway extensions have substitution effects that reduce traffic on roads and have growth effects that increase congestion on roads. Both effects should be considered in evaluating the role of subways in road congestion relief.

Finally, I find that a geographic coverage effect is necessary for the fundamental law of highway/subway congestion to hold. The expansions of the subway or highway systems not only add more capacities by building more rail lines or road lanes, but also allow people to reach more places. The geographic coverage effect measures the changes in traffic because of extensions of highway or subway geographic networks.[37] A conceptual model is proposed to study the influences of subway expansions on congestion. With the empirical results, the conceptual model indicates that the geographic coverage effect must exist and there are welfare improvements associated with subway or highway constructions. These results are consistent with the finding of Hsu and Zhang (2014) that coverage effect exists in the highway expansions in Japan.

This paper provides further evidence for the policy debates about the viability of subway systems. Subway construction is controversial because of its enormous cost. As an example, the cost of building the Second Avenue Subway in New York City, the first phase of which opened on January 1, 2017, is estimated to be roughly 2.1 billion US dollars per mile.[38] Ticket fare revenue also typically does not cover operating expenses for subway systems (APTA, 2014). In 2014, for example, fare revenue only covered 41 percent of operating expenses for the New York City subway system (National Transit Database). Most capital and operation funding gaps are filled by government subsidies. Some studies find that these subsidies are too high and cannot pass the cost-benefit analysis even after accounting for benefits in congestion savings (Stopher,

[37] The geographic coverage effect is zero if the expansion does not change the geographic coverage of highway or subway systems. If traffic does not respond to the changes of geographic coverages of subway or highway systems, the geographic coverage effect will also be zero.
[38] https://www.thoughtco.com/rail-transit-projects-costs-2798796

2004; Winston and Maheshri, 2007). However, other studies conclude subways have multiple benefits, e.g., reducing congestion (Anderson, 2014) and air pollution (Gendron-Carrier et al., 2017), and the government subsidies are welfare improving (Parry and Small, 2009; Litman, 2015). The identified effects of subways on road congestion relief in this paper should be considered in evaluating subway projects in future.

Among all public transit modes, subway should have the largest effect on road congestion. Although both subway and light rail do not interfere with road traffic, the speed of subway is much faster than light rail. A subway train can hold much more passengers than a light rail train can. Compared with changes in light rail and bus services, subway expansions have the largest potential to alleviate road congestion.

To identify the effects of subway expansions on congestion, a panel dataset for 10 (14) MSAs (cities) in US from 1991 to 2014 is constructed. With the information on VMT, PMT, road capacities, subway route miles, and population, both level regressions and first-difference models are employed to estimate the elasticity of PMT and the cross-elasticities of VMT with respect to subway route miles. To solve the reverse causality and omitted variable problem, fixed effect models and instrumental variable method are used to identify the causal effects. Following Baum-Snow (2007) and Duranton and Turner (2011), highway plans from 1947 serves as an instrument for the current highway system. In the first-difference model, long-lagged subway line length and the assignment of transportation committee members in Congress instrument for the change of subway systems, as in Gonzalez-Navarro and Turner (2016) and Knight (2005). All the model estimates show quantitatively similar results.

The rest of the paper is organized as follows. Section 2 uses a conceptual model to predict the influence of transit expansions on congestion. Section 3 introduces the empirical methods. Section 4 describes data source and summary statistics. Empirical results are in Section 5. Section 6 discusses the implications of empirical findings. Section 7 concludes.

2. A conceptual model of subway systems and road congestion

Building on the work of Holden (1989) and Hsu and Zhang (2014), a conceptual model is constructed to predict the effects of subway expansions on congestion. The model also helps study geographic coverage effect and welfare implications. This model can be applied in any context where one of the traveling alternatives is expanded.

Suppose people in a city can travel by two alternatives: r and d, representing subway and highway driving, respectively. Assume the speed of subway systems is a constant and is not correlated with passenger volume.[39] The comfort of sitting in a car is also not determined by number of vehicles on road.[40]

The comfort in subways or the speed of driving on highways (s) is a function of ridership Q and capacity K:

$$s = g(K, Q) = \begin{cases} b & Q \leq \hat{Q}(K) \\ f(K, Q) & Q > \hat{Q}(K) \end{cases}$$

$\hat{Q}(K)$ is a threshold above which the comfort in subways or the speed on highways starts to decrease with ridership.[41] When ridership is below this threshold, the comfort of taking subways or the speed on highways is a constant. Given K, the relationship between comfort/speed (s) and ridership (Q) is illustrated in Figure 1. The partial derivative of the threshold with respect to

[39] Subway operation needs to follow the predetermined time schedule. The on-time rate is above 80% for New York Subway in 2013. Equipment problems, employee errors, track repairs, and right-of-way conflicts cause two thirds of the delays. Thus, passenger volume is not a main driver of speed (see http://www.citylab.com/commute/2015/08/charting-the-new-york-subways-plunging-on-time-rate/401756/).
[40] According to a report of Department of Energy (2012), the average occupancy rate of cars in 2009 is about 1.55. It is not crowded inside a car.
[41] People get annoyed when there is no vacant seat or too crowded in subway cars or subway stations.

capacity is positive, i.e., $\partial \widehat{Q}(K)/\partial K > 0$. This means the expansions of subway or highway capacity lead to a higher threshold of congestion. The highway usage is measured by VMT, and subway ridership is represented by PMT.

The indirect utility of riding subways or driving on highways is assumed to be a function of speed/comfort (s) and coverage l. In principle, capacity expansion of a road/subway system may take either the form of lane/rail expansion or increasing the coverage by extending the length of existing routes or by creating a new route. The expansions of the subway or highway systems not only add more rail tracks or road lanes, but also allow people to reach more places. This geographic coverage effect or network effect is not captured by speed/comfort s. l measures the geographic scope of highway or subway systems. For driving, the indirect utility is represented by $U(s_d,\ l_d)$ where s_d and l_d denote the driving speeds and coverage of highway networks. Similarly, the indirect utility for subways is represented by $U(s_r,\ l_r)$ where s_r and l_r are the comfort level in subways and coverage of subway systems. The marginal utilities with respect to s and l are positive ($\partial U/\partial s > 0, \partial U/\partial l > 0$).[42]

In equilibrium, people will arbitrage between the two modes and the utility of traveling by any of the two methods should be the same: $U(s_r^0,\ l_r) = U(s_d^0,\ l_d) = U_0$.

Figure 2 shows that the initial equilibrium is at A. For a fixed number of ridership, the horizontal axis measures how the trips are allocated between the two travel alternatives. From O to P, the proportion of trips on highways increases and the share of trips in subways decreases. An implicit assumption is that subways and highways are close substitutes. The vertical axis is the utility level.[43] The utility of using highways or subways is decreasing after ridership reaches

[42] The assumption $\partial U/\partial l > 0$ can be tested. See Section 2.1.
[43] The vertical axis in Figure 2 can also be interpreted as marginal utility. At equilibrium, the marginal utility of using either of the two alternatives is the same.

the congestion threshold $\widehat{Q}(K)$. At point A, both highways and subways are congested and the utility of using any of the two modes is the same.[44] As the analysis is symmetric for highway expansions, the investigation below only focuses on the effects of building more subways.

2.1 Adding subway capacity without changing geographic coverage

Assume, for now, the subway expansion only increases capacity but does not change the geographic coverage. This means the coverage effect does not exist. A subway expansion will increase the congestion threshold as $\partial \widehat{Q}(K)/\partial K > 0$. The utility of subway riding moves to $U(s_r', l_r)$, and the system jumps to B on the graph in Figure 2, where the utility of subway riding or highway usage is higher than U_0.

As the utility at B is higher, the induced demand literature (Downs, 1962; Goodwin, 1996; Cervero, 2002) documents that people have two possible responses. First, people using other commuting routes (e.g., local roads) may switch to subways and highways. The number of people commuting by highway or subway grows. The second possibility is that people using highways and subways will do so more frequently, leaving the number of commuters unchanged, but increasing the number of trips.

Each of these cases increases total ridership. The horizontal axis extends on both sides and both utility curves shift outward. As the ridership of subways and highways increases, the utilities decline gradually. This process may continue until the extreme case occurs at C where $U(s_r^*, l_r) = U(s_d^*, l_d) = U_0$. Therefore, $s_r^* = s_r^0$ and $s_d^* = s_d^0$. The comfort levels within a subway car or station and speeds on highways are the same before and after the change of

[44] The case that only one mode is congested is less interesting. The fundamental law of congestion will fail in this case, and this is not consistent with empirical results in this paper that the law holds for both highways and subways. Hsu and Zhang (2014) have detailed theoretical analysis for the case that one mode is not congested.

subway extent. If subway expansions remove some people from highways, commuters using other modes will take their place. The empirical implication is that subway expansions have no effect on highway VMT. The fundamental law of transit congestion holds as the subway extension accompanies the same percentage increase of PMT.

It is also possible, however, that the system eventually arrives at D in Figure 2, where $U(s_r^*,\ l_r) = U(s_d^*,\ l_d) > U_0$, $s_r^* > s_r^0$, and $s_d^* > s_d^0$. At D, subways reduce congestion on highways. The fundamental law of subway congestion fails because the increase in PMT is less than the change of subway extent.

In reality, most subway expansions will extend the geographic coverage of subway systems. However, subway traffic will not respond to the changes in geographic coverage when $\partial U/\partial l = 0$. The analysis above also applies to the case that subway expansions change the geographic coverage of subway systems but agents' utility levels do not depend on geographic coverage ($\partial U/\partial l = 0$).

2.2 Subway expansions extending geographic coverage

If coverage effect exists, the subway expansion not only increases capacity, but also increases the geographic coverage.[45] The same subway expansion leads to a larger increase in utility at B on the graph in Figure 3: $U(s_r',\ l_r') > U(s_r',\ l_r)$. What follows is the same as the situation where no coverage effect exists. The extreme case is at C: $U(s_r^{*\prime},\ l_r') = U(s_d^*,\ l_d) = U_0 = U(s_r^*,\ l_r)$. The coverage effect implies $l_r' > l_r$, which further indicates $s_r^{*\prime} < s_r^* = s_r^0$. The comfort of subway riding after the expansion is worse than the initial level. This means a 1 percent expansion of subway extent leads to more than a 1 percent increase in PMT. The

[45] I assume $\partial U/\partial l > 0$ in Section 2.2. The analysis in Section 2.1 applies to the case that $\partial U/\partial l = 0$.

elasticity of PMT with respect to subway capacity is larger than one, and the fundamental law holds.[46] The subway expansion has no impact on highway usage.

If the new equilibrium is at D, the fundamental law of subway congestion can still hold because of the geographic coverage effect. At D, $U(s_r^{*\prime},\ l_r^{\prime}) > U_0 = U(s_r^0,\ l_r)$. Because of $l_r^{\prime} > l_r$, it is possible that $s_r^{*\prime} \leq s_r^0$. The elasticity of subway ridership with respect to subway expansions can be equal or greater than one. At D, adding more subway lines reduces VMT on highways because $s_d^* > s_d^0$. The fundamental law of subway congestion will fail at D if $s_r^{*\prime} > s_r^0$. Whether the law holds or not is an empirical question.

Table 1 summarizes the analysis above. Which of the four cases is true depends on the empirical evidence. In what follows, the effects of subway expansions on subway riding (PMT) and highway usage (VMT) are estimated. The estimated elasticities support case four, indicating that the geographic coverage effect exists and the utilities at the new equilibrium are improved. This also suggests that utility increases with geographic coverage ($\partial U/\partial l > 0$) and ridership responds to the extensions of geographic coverage of subway systems.

2.3 The growth effects of subway expansions

The analysis above applies to the substitution effects of subway expansions. Subway expansions may also redistribute economic activities, decentralize cities, and increase traveling demand and length of trips. This explains the positive effects of subway expansions on highway usage. Compared with the substitution effects, the growth effects may occur after a longer period as the economic activities cannot relocate instantaneously. It is easier for commuters to switch between different modes, but it takes more time to decentralize cities. The growth effects may

[46] The fundamental law of highway congestion holds when the elasticity of VMT with respect to lane miles is equal or larger than one.

increase total ridership after a longer period and shift utility curves out further in Figure 2 and Figure 3. The substitution effects of subway expansions will be weakened by the growth effects. Empirically, past subway expansions can have a positive effect on current highway traffic.

3. Empirical strategy

The main goal is to estimate the elasticities of ridership with respect to highway and subway capacities. Consider the ridership Q_{it} of city or MSA i in year t as a function of highway capacity H_{it}, subway capacity S_{it}, and city characteristics X_{it}:

$$\ln(Q_{it}) = A_0 + \rho_H^Q \ln(H_{it}) + \rho_S^Q \ln(S_{it}) + A_1 X_{it} + \epsilon_{it} \tag{1}$$

Q_{it} can denote either VMT or PMT. H_{it} is highway lane miles, and S_{it} represents directional route miles of subway systems.[47] X_{it} denotes population and other possible control variables. ϵ_{it} is an error term.

To test whether subway (highway) extensions has growth effects on highway (subway) traffic after a longer period, several 3-year lagged capacity variables ($\ln(H_{i,t-3})$ and $\ln(S_{i,t-3})$) can be included in regression. Economic activities are likely to have full response to changes of infrastructure in 3 years. Including a 4-year lag instead of a 3-year lag results in qualitatively similar results (see Table A4). π_H^Q and π_S^Q measure the growth effects of subway/highway expansions:

$$\ln(Q_{it}) = A_0 + \rho_H^Q \ln(H_{it}) + \rho_S^Q \ln(S_{it}) + A_1 X_{it} + \pi_H^Q \ln(H_{i,t-3}) + \pi_S^Q \ln(S_{i,t-3}) + \epsilon_{it} \tag{2}$$

[47] Directional route miles refer to the mileage in each direction over which public transportation vehicles travel.

For conciseness, I focus on Equation (1) to discuss the identification strategies. The same identification argument applies to Equation (2). The unbiased identification of the elasticities (ρ_H^Q and ρ_S^Q) requires exogeneity: $cov(H_{it}, \epsilon_{it}) = 0$ and $cov(S_{it}, \epsilon_{it}) = 0$. These conditions do not hold in the presence of reverse causality and omitted variable bias, both of which may be present in Equation (1) and (2). It is possible that cities choose to build more subways (or highways) in response to higher travel demand or positive population shocks. Reverse causality biases upwards the elasticity of subway PMT (or highway VMT) with respect to subway miles S_{it}. Omitted variables lead to inconsistent elasticity estimates when the ridership variable Q_{it} and capacity variables, H_{it} or S_{it}, are correlated with unobserved factors.

There are several methods to solve these endogeneity problems. The first strategy is to include city fixed effects δ_i and year fixed effects φ_t.

$$\ln(Q_{it}) = A_0 + \rho_H^Q \ln(H_{it}) + \rho_S^Q \ln(S_{it}) + A_1 X_{it} + \varphi_t + \delta_i + \epsilon_{it} \qquad (3)$$

City time-invariant characteristics are removed in Equation (3) and the identification comes from the changes of highway and subway systems over time. The city fixed effects can reduce much of the correlation between capacity variables and the error term.

A similar method is taking the first difference of the above equation to eliminate the city fixed effect term. In the first-difference model, one can still include city fixed effects (γ_i), or equivalently, city specific trend ($\gamma_i t$) in the level regressions. These fixed effects in the first difference model account for the unobserved city specific time-varying factors. Equation (4) and (5) are equivalent. Considering people may take time to respond to changes of infrastructure, a three-year first difference[48] is imposed in order to have larger variations and smaller noises in the

[48] $\Delta\ln(S_{it}) = \ln(S_{it}) - \ln(S_{i.t-3})$. If the subway expansion happens in December, a one-year first difference does not fully capture peoples' response because this response can last several months.

differenced covariates. The empirical results are robust to a one-year first-difference model and 5-year first-difference model (see Table A1 and Table A2).

$$\Delta\ln(Q_{it}) = \rho_H^Q \Delta\ln(H_{it}) + \rho_S^Q \Delta\ln(S_{it}) + A_1 \Delta X_{it} + \varphi_t + \gamma_i + \Delta\epsilon_{it} \tag{4}$$

$$\ln(Q_{it}) \quad = A_0 + \rho_H^Q \ln(H_{it}) + \rho_S^Q \ln(S_{it}) + A_1 X_{it} + \varphi_t + \delta_i + \gamma_i t + \epsilon_{it} \tag{5}$$

The last method is finding valid instrumental variables (IVs) for $\ln(H_{it})$ and $\ln(S_{it})$ in level regressions, or for $\Delta\ln(H_{it})$ and $\Delta\ln(S_{it})$ in first-difference regressions. Baum-Snow (2007) and others (Duranton and Turner, 2011; Duranton and Turner, 2012) have used the highway plan in year 1947 as an instrument for the current highway network. This instrument is valid because this historical plan was proposed to serve military purpose and to connect cities. The instrument is not correlated with local VMT or PMT. Thus, the highway plan in year 1947 is used as an instrument for the highway lane miles (H_{it}).

Valid instruments for $\ln(S_{it})$ do not appear in the literature. Instead, this paper introduces long lagged subway directional route miles and whether a city had a representative on the transportation committee of Congress as two valid instruments for the change of subways ($\Delta\ln(S_{it})$).

Suppose the following process determines the supply of subway systems:

$$\ln(S_{it}) = \alpha_0 + \alpha_1 \ln\left(S_{i,t-1}\right) + \alpha_2 X_{it} + \delta_i + \gamma_i t + \vartheta_{it} \tag{6}$$

Take the first difference:

$$\Delta\ln(S_{it}) = \alpha_1 \Delta\ln\left(S_{i,t-1}\right) + \alpha_2 \Delta X_{it} + \gamma_i + \Delta\vartheta_{it} \tag{7}$$

The lagged variable $\Delta\ln\left(S_{i,t-1}\right)$ is a good instrument for $\Delta\ln(S_{it})$ if $cov\left(\Delta\ln\left(S_{i,t-1}\right), \Delta\epsilon_{it}\right) = 0$, or in words, the lagged changes in subways are uncorrelated with the current changes of error term. Since $\Delta\ln\left(S_{i,t-1}\right) = \ln(S_{i,t-1}) - \ln(S_{i,t-2})$ and the subway levels are higly correlated, as is standard in dynamic panel model estimation, the same logic that justifies using $\Delta\ln\left(S_{i,t-1}\right)$ as an instrument also justifies using the component level or the lagged component level as an instrument. The discussion above indicates a strategy that using previous subway system extent as an instrument for current subway change. The long-lagged subway length is predetermined, so it does not correlate with the current error term. High levels of subway services in the past should predict a smaller growth rate of subway systems today. If the instrument is denoted by $\ln(S_{i,t-k})$, k is chosen to yield a strong first stage and $\ln(S_{i,t-k})$ should be a lag of $\Delta\ln(S_{i,t})$. For the three-year change $\Delta\ln(S_{i,t}) = \ln(S_{i,t}) - \ln(S_{i,t-3})$, I choose $\ln(S_{i,t-5})$ as an instrument. For the third lag of the three-year change $\Delta\ln(S_{i,t-3}) = \ln(S_{i,t-3}) - \ln(S_{i,t-6})$, I choose $\ln(S_{i,t-7})$ as an instrument. Gonzalez-Navarro and Turner (2016) use long lagged subway extent as an instrument for the changes of subway systems in studying the causal effect of subways on city growth. Results in Table 4 show that longer subway route miles in the past predict smaller growth of subway miles in subsequent periods.

The second instrument for current subway changes comes from the political economy literature. Knight (2002) uses the political power of state congressional delegations as instruments for federal grants to study whether federal funding crowds out state government spending. In a subsequent paper, Knight (2005) finds congressional districts that have representatives sitting on the transportation committee receive higher funding for highway project than districts that do not. Subway extensions usually cost significant amounts of money and federal funding is a crucial source of funding. If a city has a representative sitting on the transportation committee of the House of Representatives, it is more likely to receive federal funding to expand the subway system in the following years. Thus, whether the city had a representative on transportation committee of Congress seven years earlier is chosen as an instrumental variable for the current subway change, as the construction of subways takes many years. [49] This instrument should predict the changes of subways, but it is not correlated with current ridership in cities because the political process determines the committee assignment of representatives. Compared with the lagged subway length, this political instrument has more economic meaning and is less mechanical. The results from the first stage regressions in Table 4 confirm the significantly positive influence of political power on subway length.

To sum up, Equation (4) is the preferred first-difference-fixed-effect model that controls both time-invariant city characteristics and time-varying city specific trends. The lagged subway extent and transportation committee assignment can be employed as instruments for the changes in subway miles in Equation (4). The instrumental variable method serves as a robustness check for the first-difference-fixed-effect model.

4. Data

The information on subway service and performance is from National Transit Database (NTD). The NTD was established by Congress to be the nation's primary source for information and statistics on the transit systems in the United States. Over 660 transit providers currently report to the NTD through the Internet-based reporting system. The NTD data provides annual information on transit facilities, service levels, funding sources, revenues, and costs at Urbanized Area (UZA) and city level throughout the period 1991-2014. The NTD data also reports the directional route miles and passenger miles traveled for subway systems in different cities.

[49] The transportation committee assignment seven years ago also yields the strongest first stage.

There are 14 cities,[50] or 10 MSAs,[51] that have subway systems in the continental US.[52] All subway cities except Cleveland, OH, Lindenwold, NJ, and Staten Island, NY have experienced changes to their subway systems during the period of 1991-2014. Washington, DC, Chicago, IL, Los Angeles, CA, San Francisco, CA, and Atlanta, GA have had sizeable extensions of their subway networks between 1991 and 2014.[53] In estimating the elasticity of PMT with respect to subway route miles, city level, instead of MSA level, information is used because the sample size is larger. However, MSA level regressions show qualitatively similar results (see Table A3 in Appendix).

The level and performance data on highways and non-highway arterial roads is from the universe sample of Highway Performance Monitoring System (HPMS), which is collected by the Federal Highway Administration in the US Department of Transportation (DOT). The HPMS data is available annually since 1981. This database contains information on length (in miles), number of lanes, and the number of vehicles per lane per day for all segments of highways and non-highway arterial roads in each county. Following the method of Duranton and Turner (2011), this information is used to calculate road lane miles and VMT. Lane miles is equal to number of lanes multiplied by segment length of roads. VMT is the product of lane miles and annual average number of vehicles per lane per day.

---

[50] Los Angeles, CA, Oakland (San Francisco), CA, Washington, DC, Miami, FL, Chicago, IL, Boston, MA, New York, NY, Staten Island, NY, Baltimore, MD, Jersey City, NJ, Cleveland, OH, Philadelphia, PA, Atlanta, GA, Lindenwold, NJ. NTD reports the subway information of New York City and Staten Island separately, and I treat Staten Island as a city here. The subway in Staten Island is not connected to NYC subway directly. These 14 cities are in 10 MSAs.

[51] New York, NY, Staten Island, NY, Jersey City, NJ are in one MSA. Washington, DC and Baltimore, MD are in one MSA. Philadelphia, PA and Lindenwold, NJ are in one MSA. Each of the rest cities are in one MSA.

[52] The subway systems in this paper refer to heavy rail systems in NTD. Part of a heavy rail system can be above ground. The heavy rail systems typically have higher speeds and capacities. See the following link for comparisons between heavy rail and light rail: http://designlightrail.com/lightrailcompare/

[53] Washington, DC had gradually increased its total subway directional route miles by 56 miles between 1991 and 2005. Chicago built 15-miles subway between 1990 and 2000. Los Angeles built 31.9 directional route miles subway between 1993 and 2000. San Francisco and Oakland extended subway system by 67 directional route miles between 1995 and 2003. Atlanta saw an increase of 25 miles from 1993 to 1999.

The HPMS data displays the route number of interstate highways. To differentiate different types of highways, the three-digit interstate highways (e.g., 690, 481) are called ring highways, which are circumferential or spur highways that principally serve local urban areas. Similarly, radial highways denote the one- or two-digit interstate highways (e.g., 90, 81) that connect different MSAs. The definition of interstate highways in this paper include both ring highways and radial highways. The non-highway arterial roads include non-highway principal arterials and minor arterials. These roads typically serve major centers of MSAs and are not access-controlled.[54] The 1999 Metropolitan Statistical Area (MSA) definitions are used to link the counties to MSAs. The HPMS data also report the urban/rural status of each segment of roads. On average, 90 percent of the interstate highway traffic (VMT) in MSAs occurs in the urban portion of MSAs. Because all subway systems are in urban areas, the road segments in the urban portion of each MSA are used to calculate road capacity and performance variables. To maintain comparability between the results in this paper with the results in Duranton and Turner (2011), the MSA level information is used to estimate the cross-elasticity of road VMT with respect to subway route miles.

The annual county and city population data is from the Census. MSA populations come from the summation of county populations. Historical Congressional committee assignments of representatives are from Stewart and Woon (2016). A congressional districts' map is overlaid with a map of cities to obtain correspondence between cities and congressional districts. This crosswalk helps calculate whether a city has had a representative on the House transportation committee in each year.

[54] Access-controlled means limited or no access to adjacent property. Interstate highways in US are access-controlled. A detailed description of the functional class of roads: https://www.fhwa.dot.gov/planning/processes/statewide/related/highway_functional_classifications/section03.cfm

Table 2 displays the summary statistics of PMT, VMT, and capacity measures of subways, highways, and non-highway arterial roads. For all variables except transportation committee assignment, the temporal variation is much smaller than the standard deviation and cross section variation. The VMT is far larger than PMT, confirming that transit ridership only accounts for a small fraction of total miles traveled. The length of ring highways is about 42 percent of the total interstate highway length, indicating the radial highways account for 58 percent of the total interstate highway lane miles.

5. Results

Level regressions with fixed effects, first-difference models with and without fixed effects, and 2SLS are used to study the elasticities of subway and highway ridership with respect to subway route miles.

5.1 The elasticity of subway PMT with respect to subway route miles

5.1.1 OLS and fixed effect models

Table 3 displays the regression results obtained by estimating the elasticity of subway PMT with respect to subway route miles and road lane miles for three different types of roads in 14 cities.[55] Specifically, the regression includes interstate highway lane miles, ring highway lane miles, and non-highway arterial road lane miles as regressors to study the substitution effects of

[55] All standard errors are robust to heterogeneity and serial correlation. I also generate the standard errors using a wild cluster bootstrap method developed by Cameron et al. (2008). It turns out the bootstrapped standard errors (1000 repetitions) are generally no larger than the robust standard errors. Thus, I only report results with robust standard errors.

roads on subway PMT. [56] The third lag of log subway and road capacity levels are also included to identify the growth effects.

Column (1) reports results using a level regression with city fixed effects. The estimated elasticity of PMT to subway extent is significantly larger than one. Column (3) shows the results using the 3-year first-difference model and the elasticity is still larger than one. Ring interstate highways significantly reduce subway miles traveled. Column (4) results are obtained taking accounts of the time-varying city specific trends by including city fixed effects in the first-difference model. The estimated elasticity is 0.97, which is very close to unity.

Columns (2), (5), and (6) display the results including the lagged subway and road capacity variables. The model specification in column (6) is preferred, as it removes all city invariant factors and controls for city specific trends. All three specifications show similar results, however. The unit elasticity result still holds. The coefficient for the ring highway miles variable is significantly negative, indicating ring highways reduce subway PMT. Subway extensions made three years ago have a significant positive effect on current subway traffic. If a city added 10 percent more subways route miles three years ago, the current subway PMT has increased by 5.7 percent. There are two possible explanations for this lagged effect. First, people and economic activities may take time to respond to the changes of infrastructure. Second, subway expansions decentralize cities. Under a dispersed city structure, people have to commute longer distances. The expansions of interstate highways and ring highways in the past have positive effects on current subway PMT, although the coefficients are not significant. The negative coefficient on the lagged non-highway arterial road capacity variable indicates that

[56] Baum-Snow et al. (2016) show that the decentralization effects on population and GDP vary across types of road in China. Compared with radial highways, ring highways are found to have larger effects.

expanding non-highway arterial road capacity reduces current subway usage. It seems that building more non-highway arterial roads only substitute traffic from subways.

5.1.2 Instrumental variable results

Instrumental variables are further used to identify the causal effects of subway route miles on PMT. The first stages of the 2SLS are presented in Table 4. Columns (1) and (2) are first stage regressions using transportation committee assignment seven years ago and the fifth-year lag of log subway miles as instruments for the three-year changes of subway systems in 14 cities. If a city had a representative on the transportation committee seven years ago, it is more likely to receive federal funding and experience subway extensions today. The five-year-lagged variable for subway miles also predicts well the current changes in subway miles. If the level of subway miles in the past was high, the current change of subway miles is smaller. Both instruments are strong with first-stage F statistics larger than ten.

Table 5 displays the second stage results. Column (1) reports results for ln(PMT) when the transportation committee assignment variable is used as an instrument for the change of subway extent. The results support a unit elasticity. Adding more ring highways leads to fewer subway miles traveled and the coefficient of -0.13 is statistically significant. Column (2) results are based on using the subway length five years ago as an instrumental variable. All regression coefficients are similar to Colum (1). Column (3) uses both instruments, which enable me to do over-identification tests. The two instruments pass both Sargan and Basmann over-identification tests, confirming the validity of the instruments.[57] Compared with the transportation committee assignment in Congress instrument, the lagged subway miles is a mechanical instrument, but it is

[57] For space and conciseness, Table 5 only displays Sargan test results. The Basmann test result is similar.

valid and strong. Column (4) results further control the lagged capacity variables, and the evidence here is consistent the results reported in column (6) in Table 3. Overall, the empirical findings in Table 5 support the results in Table 3.

In summary, the OLS, fixed effect, and 2SLS models support a unit elasticity of subway ridership with respect to subway extent. This unit elasticity confirms that the fundamental law of subway congestion holds. Extending the subway networks will not mitigate the congestion in subways, just as Duranton and Turner (2011) find that building more highways does not reduce highway congestion. Ring highways can replace subway traffic and the cross elasticity is around -0.13.

5.2 The cross-elasticity of road VMT with respect to subway expansions

This section reports results on whether adding more subway route miles in city affects VMT on highways and non-highway arterial roads. To compare with studies in literature, all analysis in this subsection is conducted at MSA level.

5.2.1 The effect on VMT on interstate highways

Table 6 shows the results of regressing interstate highway VMT on interstate highway and subway capacity variables. Column (1) reports results using level variables in an empirical model with fixed-effects. The estimated elasticity of VMT with respect to highway lane miles is larger than unity, confirming the fundamental law of highway congestion. The coefficient for subway route miles indicates that subway route miles have no significant effect on highway VMT. Columns (3) and (4) show results using first-difference models first without and then with MSA fixed effects. Column (4) controls for time varying city-specific unobserved factors. All specifications confirm a unit elasticity of VMT to highway lane miles, which is consistent with Duranton and Turner (2011). No significant effect of subway route miles on VMT is found.

Columns (2), (5), and (6) of Table 6 display results from a model including the lagged highway and subway variables. All three regressions show that the lagged subway route miles has a positive effect on current highway usage and this elasticity is about 0.09. Therefore, an expansion of 10 percent in subway directional route miles today will lead to an increase of 0.9 percent in future highway VMT. These results indicate that the new subway lines take time to redistribute economic activity and decentralize cities. If the economic activities are less densely distributed, commuting distances become longer and VMT increase.

The IV estimation results in Table 7 are consistent with the results reported in Table 6. The IV estimation uses subway route miles five years ago and seven years ago as instruments for the changes in subway route miles at time t and time t-3.[58] The 1947 highway plan variable is adopted to instrument for current highway system. The first stages are presented in Table 4. Longer route miles in the past predict lower growth of subway length today. The first stages are strong with F statistics far larger than ten. The corresponding second stages are reported in Table 7. The results reported in column (1) instrument the current highway network with a historical highway plan, and the coefficient measuring the effect of highway miles on VMT is 0.72. Duranton and Turner (2011) report that this elasticity is 1.03 after analyzing all the MSAs using data for 1983, 1993, and 2003. The difference between my estimate and their finding may result from two reasons. First, the sample is different as I focus on subway MSAs in the years of 1991-

[58] The transportation committee assignment of representatives is weak in power (first stage F statistics lower than ten. See Table A3) for instrumenting the changes of subways miles in MSAs, although it is strong for instrumenting the changes of subway miles in cities (Section 5.1.2). Thus, I only use the lagged subway miles as instruments in the first-difference model. The over-identification tests in Section 5.1.2 support that the lagged subway miles are valid instruments. Nevertheless, the second stage results are similar when I use transportation committee assignment of representatives to instrument the changes of subway length in 10 MSAs.

2014. Second, the instrument might not be valid for only ten subway MSAs. When I estimate a similar 2SLS regression using all MSAs, I find the elasticity for VMT with respect to highway miles to be 0.98, which is close to Duranton and Turner's (2011) elasticity estimate. The results in columns (2) and (3) instrument the current change of subway route miles and its lagged values using subway route miles five and seven years ago. Subways in the past improve current highway traffic and have no significant effect on contemporaneous highway traffic. The results reported in column (4) instrument $\Delta\ln(S)_t$ and $\Delta\ln(S)_{t-3}$ simultaneously, and the coefficient that measures the effect of subway route miles on VMT becomes insignificant.

From these results, there is strong evidence that the VMT with respect to highway capacity elasticity is equal to one. Additional subway route miles do not lead to fewer VMT but increase VMT on interstate highways with a three-year lag. The empirical results also suggest that compared with highway extensions, people may take more time to respond to the change of subways, as the third lag of log subway length has a positive effect on PMT, while the third lag of highway length has no significant effect on VMT. These differences suggest that there might be much heterogeneity in the response times to the changes of different infrastructures.

As mentioned in Section 2, the substitution effects of subways on highway usage would be small if these two modes are not close substitutes. Compared with interstate highways, ring highways are closer substitutes, as subways and ring highways share similar geographic coverages. Thus, subway expansions may have more prominent substitution effects on ring highway usage.

5.2.2 The effect on VMT on ring highways

Table 8 and Table 9 display regression estimates for ring highway VMT using OLS, fixed effect, and 2SLS models, similar to the estimation strategy used for interstate highways. All specifications find the elasticity of VMT with respect to ring highway capacity is significantly larger than one, which is consistent with the result in Hsu and Zhang (2014). Different from the unit elasticity estimate for all MSAs in Duranton and Turner (2011), the elasticity in subway MSAs is larger, indicating a greater behavioral response to changes in ring highway systems in larger cities. The 1947 highway plan is not a strong instrument for current ring highway system. This makes intuitive sense, as the historical plan is for highways that connects different MSAs (radial highways), not for ring highways within a MSA. The results reported in column (1) in Table 9 should be interpreted with caution, as the results may suffer from weak IV problem. However, the long-lagged subway levels are strong instruments for the current changes of ring subways.

All first-difference models indicate that contemporary subway expansions have a significantly negative effect on ring highway usage and this cross elasticity is around -0.08. Therefore, building more subways will reduce the congestion on ring highways. The lagged subway extent variables still predict more ring highway PMT today, although the magnitude is much smaller (the elasticity is about 0.04). The growth effect is smaller than the substitution effect. All these estimates are robust to the 2SLS results.

The analysis in section 5.2.1 and 5.2.2 indicate that subway systems reduce contemporaneous traffic on ring highways but have no significant effect on contemporaneous traffic on interstate highways. As interstate highways include ring highways and radial highways, I expect subway expansions will not reduce traffic on radial highways. Radial highways have higher travel speed and more extensive geographic coverage, so they are not close substitutes for subway systems.

5.2.3 The effect on VMT on radial highways

Table 10 displays the results of regressing radial highway VMT on subway route miles. Both the level and the first difference regressions show that subway systems do not reduce contemporaneous radial highway usage, but have a lagged and significantly positive effect on radial highway VMT. This growth effect (0.17) is much larger than the estimates for interstate highways (0.08) and ring highways (0.04). The empirical results support that subway systems do not reduce traffic on radial highways and will increase traffic on radial highways in future.

Compared with ring highways, non-highway arterial roads are even better substitutes for subways as they have similar geographic coverages and travelling speed. Subways should have the largest substitution effects on usage of non-highway arterial roads.

5.2.4 The effect on VMT on non-highway arterial roads

Tables 11 and 12 exhibit the regression results for non-highway arterial roads. The 1947 highway plan and long lagged subway extent are used as instruments for current non-highway arterials and current change of subways. Consistent with Duranton and Turner (2011), the own-elasticity of arterial road usage with capacity is 0.87, which is significantly less than one. The fundamental law of arterial road congestion fails because building 1 percent more arterial roads leads to a less than 1 percent increase in traffic. The results in column (1) in Table 12 show a negative estimate of the elasticity, but the instrument (highway plan in year 1947) is not strong.

The cross-elasticity of arterial road VMT with respect to subway route miles is significantly negative. The magnitude is around -0.14. Expanding subways by 10 percent will reduce congestion on non-highway arterial roads by 1.4 percent. Therefore, both building more arterial roads and subways eliminate congestion on arterial roads. These findings are robust to all specifications, including the instrumental variable results (column 2-4 in Table 12). As expected, the relief effect of subways on non-highway arterial roads is much larger than that of ring highways and interstate highways. No growth effect exists, as subway expansions in the past have no significant effect on VMT of non-highway arterial roads.

6. Discussion

6.1 The substitution and growth effects of subway expansions

Duranton and Turner (2011) find that bus transit has no significant impact on interstate highway (including both radial highways and ring highways) usage and conclude that public transit will not alleviate highway congestion. The model in Section 2 and empirical evidence in this paper suggest the reason for their findings is that public transit is not a good substitute for interstate highways, especially for radial highways connecting different MSAs. Using the data for MSAs with subway systems, this paper confirms that subway expansions have no significant substitution effect on interstate highway VMT. However, I do find that adding more subway route miles significantly decreases the contemporaneous traffic on ring highways and non-highway arterial roads. These findings echo those of Anderson (2014) that the delay on highways that are parallel to subway lines increases 47 percent when subway service ceases during a transit worker strike in Los Angeles. My findings here also explain the conclusions of Gendron-Carrier et al. (2017) that subway systems reduce air pollution. What I discover here reconciles the current literature. It is important to consider the heterogeneous effects of subway systems on different types of roads.

Non-highway arterial roads share at least two similar attributes with subways: small geographic coverages and low traveling speeds. Even though ring highways have high speed limits, they have similar geographic coverages to subways. However, radial highways share no similarities with subways due to large geographic coverages and faster speeds. My empirical evidence is consistent with the coverage and speed patterns, because subway expansions reduce VMT much more on non-highway arterial roads than on ring highways. As well, building more subways has no substitution effect on VMT on interstate and radial highways.

Additional subway miles may also have long run effects on road miles in two ways: additional subway miles could cause population growth in the city and/or added miles could induce population decentralization and thus longer commutes. Both could lead to more vehicle miles as well as more transit miles. If subways do not cause city to grow, as Gonzalez-Navarro and Tuerner (2016) suggest, the positive effects of subways on radial and ring highway VMT may come from the redistribution of economic activities within the MSA. In a more dispersed city structure, people could travel more miles on highways. The current studies (Nelson et al., 2007; Parry and Small, 2009; Anderson, 2014) analyzing the effects of subways on road congestion generally neglect this growth effect. Although subways have both reducing and growth effects on ring highway traffic, the net effect of subway expansions should reduce traffic on ring highways, as the reducing effect dominates the growth effect.

6.2 The substitution and growth effects of road extensions

If adding more subway miles substitute traffic from roads, building more roads may also have a similar substitution effects. There is a symmetric substitution effect of ring-highway expansions on subway PMT. A 10 percent increase in ring highway lane miles decreases subway

PMT by 1.3 percent. However, this substitution effect is much smaller for non-highway arterial roads. Building 10 percent more non-highway arterial roads three years ago only reduces current subway PMT by 0.6 percent, and the contemporaneous changes of non-highway arterial roads have no significant impact on subway PMT. This is inconsistent with the expectation that non-highway arterial roads are the closest substitutes for subways and should have the largest substitution effect. One possible explanation is the empirical finding that the fundamental law of road congestion does not apply to non-highway arterial roads. This indicates non-highway arterial roads are not congested,[59] so people's preference for non-highway arterial roads is not as strong as the preferences for subways and ring highways. Therefore, the extensions of arterial roads do not substitute many traffic from other travel modes. This may explain why non-highway arterial roads have weak substitution effects on subway PMT.

Expansions of radial or ring highways could decentralize cities and lead to longer trips. If there is a symmetric growth effect of highway expansions, subway PMT should increase after adding more highway miles. However, the empirical results find no significant effect of past highway expansions on current subway PMT. The reason for this contradiction might be that subway only accounts for less than 1 percent of total trips in US and the effect of highway expansions on subway PMT is too small to identify.[60]

6.3 The existence of geographic coverage effect

Table 1 displays four cases summarizing the possible consequences of subway extensions. The empirical findings support case four where the fundamental law of subway

[59] The model in Hsu and Zhang (2014) shows that the failure of the fundamental law of non-highway arterial road congestion indicates that non-highway arterial roads are not congested. See Hsu and Zhang (2014) for detail.
[60] Highways decentralize cities and make length of trips longer, but the subway PMT may change little because of the tiny share of subways ridership in total trips. Table 2 shows that subway PMT is less than 1 percent of VMT on highways.

congestion holds and subways replace traffic on ring highways and non-highway arterial roads. Thus, traffic responds to the changes of geographic coverage (coverage effect exists and $\partial U/\partial l > 0$) and the utilities of both driving and subway riding are improved. The same logic applies to ring highway expansions. The results in Table 5 and Table 9 show that ring highways shift people from subways and the fundamental law of ring highway congestion holds. Therefore, coverage effects also appear in ring highway extensions. The welfare implication is that constructing more subways and ring highways will reduce congestion and increase utilities of using these two modes.

Building more subway lines will reduce traffic on ring highways, thus increase speed, but will not influence ring highways' geographic coverage. If the fundamental law of ring highway congestion holds without coverage effect, subway extensions should have no effect on ring highway traffic. If subways shift some people away from ring highways, other travelers would take their place (Duranton and Turner, 2011). The empirical findings support the congestion relief effect of subways, however. Thus, the existence of fundamental law of ring highway congestion requires the geographic coverage effect. Both higher speeds and coverage effect lead to more ridership. The effect of faster speed alone is not large enough to make traffic increase the same percentage when highway lane miles grow by one percent. One corollary is that the law may not hold for highway extensions only adding more lanes and not changing the geographic coverage. Conducting empirical analysis for this prediction is beyond the scope of this paper due to data limitations.[61]

[61] To test this corollary, the data should have a unique identification code for each road segment across time, so I can track the change of lanes for this road segment. The HPMS data has a unique identification code for each road segment in each year, but this code varies across time. The HPMS data is not a panel for each road segment.

6.4 The fundamental law of congestion also applies to bus and rail

Tables 3, 4, and 5 confirm that the PMT increases one for one with subway route miles. This indicates the universality of the fundamental law of congestion. A subsequent question is whether the law holds for all transit modes, including bus and rail. Table A5 displays the results of regressing rail PMT on rail miles and regressing bus PMT on number of buses. Both the fixed effect model and IV model show that the estimated elasticities are one or greater, demonstrating that the law holds for other transit modes. Table A6 also shows that bus transit is complementary to rail transit, while the expansions of both subway and rail networks substitute traffic from bus transit.

7. Conclusions

This paper estimates the elasticity of subway PMT and highway VMT to subway route miles by analyzing US subway cities and MSAs between the years 1991 and 2014. A theoretical model is proposed to analyze the effect of subway (highway) expansions on congestion. OLS, fixed effect model, and 2SLS are used in level and first-difference regressions to calculate the estimates.

The elasticity of subway PMT with respect to subway route miles is 1.27, which demonstrates that the fundamental law of road congestion also applies to subways. Robustness checks show that the law also holds for rail and bus. Subway expansions have both substitution and growth effects on road traffic. Subways are found to reduce traffic on roads that are close substitutes (ring highways and non-highway arterial roads). A 10 percent expansion of subway length reduces contemporaneous traffic on ring highways and non-highway arterial roads by 0.7 percent and 1.4 percent. Past subway extensions increase highway traffic today. A 10 percent increase in subway capacity three years ago leads to a 0.4 percent increase in VMT on ring highways and to a 1.7% percent increase in VMT on radial highways. The lagged effects of subway expansions on VMT appear to result from the effect of subway expansions on decentralization of economic activities in cities and longer commutes. Taking both the short run effects and long run effects into consideration, subways reduce traffic on ring highways and non-arterial roads, but increases congestion on radial highways.

Combined with the theoretical results, the empirical evidence predicts the existence of coverage effect and welfare improving effect of subway expansions. The coverage effect is necessary for the fundamental law of highway/subway congestion.

The findings of this paper provide evidence that can be used in cost-benefit analysis of subway projects. The estimated elasticity of subway usage to subway extent helps to predict the trend of ridership. The estimated elasticities of VMT with respect to subway route length indicate the potential gains in congestion relief, which is one of the benefits of providing more subways. The policy makers have to consider the different effects of subway extensions on congestion levels on different types of roads. The benefit in congestion relief is the largest for non-highway arterial roads. Subways are not useful for reducing congestion on radial highways. The benefits identified in this paper are lower bounds, however, as the effects on local roads' congestion are not studied.

Subways may have an even larger substitution impact on local road traffic. The HPMS data has lots of missing values for the VMT of local roads, so it is beyond the scope of this paper to identify the impacts of subway expansions on VMT of local roads. The other public transit modes, including rail and bus, also deserve further analysis. These plausible extensions are left for future research.

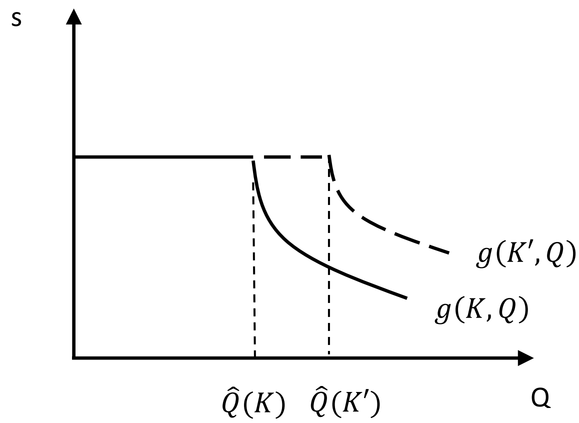


Figure 1: The effect of capacity expansions on speed or comfort

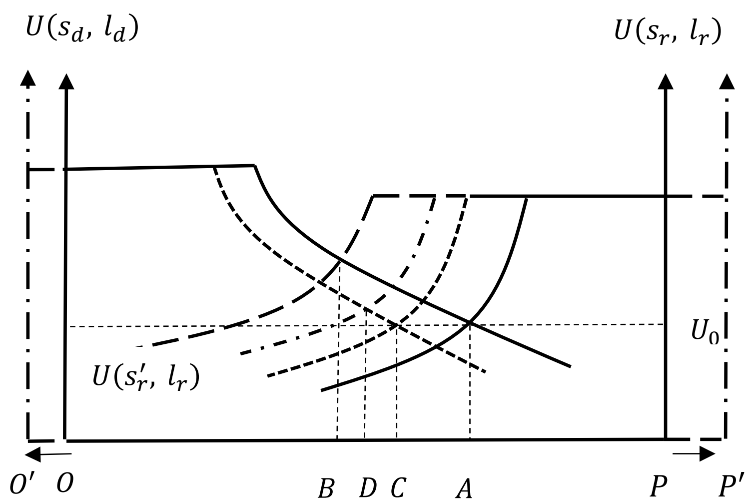


Figure 2: The effect of subway expansions (no geographic coverage effect)

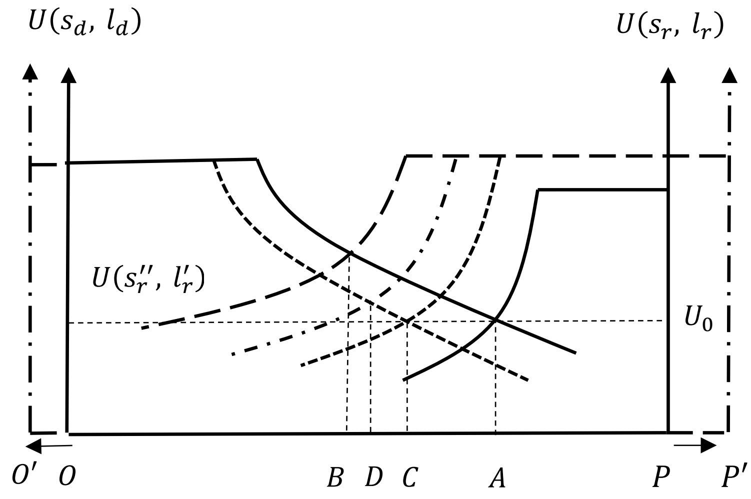


Figure 3: The effect of subway expansions (geographic coverage effect)

Table 1: Summarization of the effects of subway expansions

Cases	Existence of geographic coverage effect and $\partial U/\partial l > 0$	Utility is increased ($U' > U_0$)	The fundamental law of subway (road) congestion holds	Subway (road) expansions reduce highway (subway) usage
1	No	No	Yes	No
2		Yes	No	Yes
3	**Yes**	No	Yes	No
4		**Yes**	**Yes** or No	**Yes**

Table 2: Summary statistics for subway and road capacities and performance (1991-2014)

Variables	Mean	Standard Deviation	Cross section	Temporal variation
PMT (in Ms)	949	2080	2100	459
Subway route miles	104	123	127	10.0
Transportation committee	0.39	0.56	0.38	0.42
VMT (IH, in Ms)	114980	78470	79930	19820
Lane miles (IH)	2428	1197	1212	324
VMT (RH, in Ms)	49270	43800	44900	10040
Lane miles (RH)	1008	600	608	158
VMT (non-highway arterial, in	69350	48540	43430	25370
Lane miles (non-highway arterial)	9939	6715	5982	3571

[1]Ms denotes millions. PMT is annual passenger miles traveled. VMT is annual vehicle miles traveled. IH refers to interstate highways. RH denotes ring highways. The summary statistics are for subway cities/MSAs.

[2] Transportation committee assignment is equal to 1 if the city has a representative on board. 0 otherwise.

Table 3: ln(Passenger miles traveled) of **Subways** (OLS, 1991-2014)

	(1)	(2)	(3)	(4)	(5)	(6)
	Level		3-year difference			
VARIABLES	City FE	City FE	OLS	City FE	OLS	City FE
ln(Subway miles)$_t$	1.65***	0.80***				
	(0.074)	(0.18)				
ln(IH lane miles)$_t$	0.19	0.34***				
	(0.12)	(0.092)				
ln(RH lane miles)$_t$	-0.18*	-0.25***				
	(0.097)	(0.075)				
ln(NHAR lane miles)$_t$	-0.040	-0.053				
	(0.044)	(0.037)				
ln(Subway miles)$_{t-3}$		0.66***				
		(0.13)				
ln(IH lane miles)$_{t-3}$		-0.28				
		(0.18)				
ln(RH lane miles)$_{t-3}$		0.31				
		(0.22)				
ln(NHAR lane miles)$_{t-3}$		-0.00067				
		(0.045)				
Δln(Subway miles)$_t$			1.19***	0.97***	0.99***	0.97***
			(0.18)	(0.17)	(0.13)	(0.14)
Δln(IH lane miles)$_t$			0.049	-0.016	0.12	0.096
			(0.090)	(0.10)	(0.080)	(0.088)
Δln(RH lane miles)$_t$			-0.12**	-0.089	-0.15***	-0.14**
			(0.056)	(0.062)	(0.054)	(0.058)
Δln(NHAR lane miles)$_t$			0.016	0.034	0.033	0.056
			(0.023)	(0.041)	(0.032)	(0.036)
Δln(Subway miles)$_{t-3}$					0.61***	0.57***
					(0.17)	(0.19)
Δln(IH lane miles)$_{t-3}$					0.013	0.10
					(0.24)	(0.26)
Δln(RH lane miles)$_{t-3}$					0.16	0.10
					(0.28)	(0.29)
Δln(NHAR lane miles)$_{t-3}$					-0.040	-0.057**
					(0.026)	(0.025)
City FE	14	14	-	14	-	14
Observations	328	286	286	286	244	244
R-squared	0.991	0.993	0.509	0.564	0.583	0.610

[1] IH denotes interstate highways. RH refers to ring highways. NHAR annotates non-highway arterial roads. Year fixed effects are included in all regressions. City population is controlled but not listed.

[2]Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: First stage regression results of instrumenting for changes of subway miles

	(1)	(2)	(3)	(4)	(5)
	14 Cities			10 MSAs	
VARIABLES	$\Delta\ln(S)_t$	$\Delta\ln(S)_t$	$\ln(IH)_t$	$\Delta\ln(S)_t$	$\Delta\ln(S)_{t-3}$
Representative on transportation committee of Congress 7 years ago (=1 if yes, 0 otherwise)	0.10*** (0.029)				
Subway route miles 5 years ago		-0.58*** (0.089)		-0.54*** (0.086)	
Highway plan in 1947			0.55*** (0.081)		
Subway route miles 7 years ago					-0.48*** (0.084)
City/MSA FE	14	14	-	10	10
F statistics for instruments	12.42	39.68	46.35	39.76	34.14
Observations	261	258	237	232	228
R-squared	0.445	0.797	0.903	0.760	0.734

[1]The change is a three-year difference, i.e., $\Delta\ln(S)_t = \ln(S)_t - \ln(S)_{t-3}$.
[2]Controlled but not listed variables: year fixed effects, change of population and its lag, change of highway lane miles and its lag.
[3]Robust standard errors in parentheses. Standard errors are clustered at MSAs for using highway plan 1947 as an IV. *** p<0.01, **p<0.05, *p<0.1.

Table 5: ln(Passenger miles traveled) of **Subways** (2SLS, 1991-2014)

	(1)	(2)	(3)	(4)
VARIABLES	IV1 for $\Delta\ln(S)_t$	IV2 for $\Delta\ln(S)_t$	Both IVs for $\Delta\ln(S)_t$	Both IVs for $\Delta\ln(S)_t$
$\Delta\ln(\text{Subway miles})_t$	1.06***	1.27***	1.27***	1.04***
	(0.26)	(0.26)	(0.26)	(0.17)
$\Delta\ln(\text{IH lane miles})_t$	-0.0099	0.018	0.018	0.098
	(0.096)	(0.094)	(0.094)	(0.081)
$\Delta\ln(\text{RH lane miles})_t$	-0.13**	-0.11*	-0.11*	-0.13**
	(0.060)	(0.059)	(0.059)	(0.052)
$\Delta\ln(\text{NHAR lane miles})_t$	0.092	0.030	0.030	0.047
	(0.065)	(0.050)	(0.050)	(0.034)
$\Delta\ln(\text{Population})_t$	0.92***	0.90**	0.90**	0.53
	(0.33)	(0.36)	(0.36)	(0.35)
$\Delta\ln(\text{Subway miles})_{t-3}$				0.56***
				(0.17)
$\Delta\ln(\text{IH lane miles})_{t-3}$				0.11
				(0.24)
$\Delta\ln(\text{RH lane miles})_{t-3}$				0.091
				(0.27)
$\Delta\ln(\text{NHAR lane miles})_{t-3}$				-0.059**
				(0.023)
City FE	14	14	14	14
F statistics of first stage	12.42	39.68	39.62	85.35
p-value of over-identification test	-	-	0.32	0.72
Observations	261	258	258	244
R-squared	0.572	0.503	0.503	0.609

[1]IH denotes interstate highways. RH refers to ring highways. NHAR annotates non-highway arterial roads. Year fixed effects are included in all regressions.
[2]IV1 is whether the city has a representative on transportation committee of Congress 7 years ago. IV2 is subway miles 5 years ago. The change is a three-year difference, i.e., $\Delta\ln(S)_t = \ln(S)_t - \ln(S)_{t-3}$.
[3]Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: ln(Vehicle miles traveled) on **Interstate Highways** (OLS, 1991-2014)

	(1)	(2)	(3)	(4)	(5)	(6)
	Level		3-year difference			
VARIABLES	MSA FE	MSA FE	OLS	MSA FE	OLS	MSA FE
ln(IH lane miles)$_t$	1.13***	1.10***				
	(0.033)	(0.046)				
ln(Subway miles)$_t$	0.00046	-0.036				
	(0.012)	(0.028)				
ln(Population)$_t$	0.19**	0.14*				
	(0.082)	(0.080)				
ln(IH lane miles)$_{t-3}$		0.23**				
		(0.098)				
ln(Subway miles)$_{t-3}$		0.050***				
		(0.019)				
Δln(IH lane miles)$_t$			1.10***	1.08***	1.11***	1.09***
			(0.052)	(0.060)	(0.049)	(0.057)
Δln(Subway miles)$_t$			-0.023	-0.018	-0.044*	-0.031
			(0.016)	(0.024)	(0.023)	(0.026)
Δln(Population)$_t$			0.24	0.20	0.23	0.19
			(0.18)	(0.20)	(0.18)	(0.20)
Δln(IH lane miles)$_{t-3}$					0.030	0.0057
					(0.073)	(0.063)
Δln(Subway miles)$_{t-3}$					0.066***	0.090***
					(0.017)	(0.024)
MSA FE	10	10	-	10	-	10
Observations	237	234	234	234	231	231
R-squared	0.996	0.996	0.879	0.883	0.882	0.887

[1]IH refers to interstate highways. Year fixed effects are included in all regressions.
[2]Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: ln(Vehicle miles traveled) on **Interstate Highways** (2SLS, 1991-2014)

	(1)	(2)	(3)	(4)
	Level	3-year difference		
VARIABLES	IV for $\ln(IH)_t$	IV for $\Delta\ln(S)_t$	IV for $\Delta\ln(S)_{t-3}$	IVs for $\Delta\ln(S)_t$ and $\Delta\ln(S)_{t-3}$
$\ln(\text{IH lane miles})_t$	0.74***			
	(0.22)			
$\ln(\text{Subway miles})_t$	-0.097			
	(0.064)			
$\ln(\text{Population})_t$	0.36			
	(0.24)			
$\Delta\ln(\text{IH lane miles})_t$		1.08***	1.09***	1.09***
		(0.056)	(0.052)	(0.054)
$\Delta\ln(\text{Subway miles})_t$		0.042	-0.040	0.019
		(0.032)	(0.037)	(0.081)
$\Delta\ln(\text{Population})_t$		0.20	0.19	0.19
		(0.18)	(0.18)	(0.18)
$\Delta\ln(\text{IH lane miles})_{t-3}$			0.0061	0.0061
			(0.058)	(0.058)
$\Delta\ln(\text{Subway miles})_{t-3}$			0.089**	0.062
			(0.037)	(0.062)
MSA FE	-	10	10	10
F statistics of first stage	27.48	39.76	61.97	-
Observations	237	232	230	230
R-squared	0.848	0.882	0.887	0.886

[1]IH refers to interstate highway. IV for current highway lane miles is highway plan in year 1947. IVs for $\Delta\ln(S)_t$ and $\Delta\ln(S)_{t-3}$ are subway miles in year t-5 and year t-7. Year fixed effects are included in all regressions.

[2]Robust standard errors in parentheses. Clustered standard errors at MSAs for (1). *** p<0.01, ** p<0.05, * p<0.1.

Table 8: ln(Vehicle miles traveled) on **Ring Highways** (OLS, 1991-2014)

	(1)	(2)	(3)	(4)	(5)	(6)
	Level		3-year difference			
VARIABLES	MSA FE	MSA FE	OLS	MSA FE	OLS	MSA FE
$\ln(\text{RH lane miles})_t$	1.20***	1.19***				
	(0.070)	(0.074)				
$\ln(\text{Subway miles})_t$	-0.025*	-0.050				
	(0.014)	(0.032)				
$\ln(\text{Population})_t$	0.030	0.013				
	(0.096)	(0.100)				
$\ln(\text{RH lane miles})_{t-3}$		0.25***				
		(0.054)				
$\ln(\text{Subway miles})_{t-3}$		0.065***				
		(0.019)				
$\Delta\ln(\text{RH lane miles})_t$			1.21***	1.21***	1.19***	1.19***
			(0.071)	(0.066)	(0.080)	(0.077)
$\Delta\ln(\text{Subway miles})_t$			-0.091***	-0.088***	-0.061***	-0.067**
			(0.021)	(0.022)	(0.020)	(0.022)
$\Delta\ln(\text{Population})_t$			1.22***	1.24***	0.19	0.86**
			(0.13)	(0.14)	(0.19)	(0.36)
$\Delta\ln(\text{RH lane miles})_{t-3}$					0.011	0.0092
					(0.060)	(0.057)
$\Delta\ln(\text{Subway miles})_{t-3}$					0.047***	0.039*
					(0.018)	(0.020)
MSA FE	10	10	-	10	-	10
Observations	237	234	234	234	228	228
R-squared	0.997	0.998	0.934	0.945	0.943	0.947

[1]RH refers to ring highways. Year fixed effects are included in all regressions.
[2]Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: ln(vehicle miles traveled) on **Ring Highways** (2SLS, 1991-2014)

	(1)	(2)	(3)	(4)
	Level	3-year difference		
VARIABLES	IV for $\ln(RH)_t$	IV for $\Delta\ln(S)_t$	IV for $\Delta\ln(S)_{t-3}$	IVs for $\Delta\ln(S)_t$ and $\Delta\ln(S)_{t-3}$
$\ln(\text{RH lane miles})_t$	1.12***			
	(0.28)			
$\ln(\text{Subway miles})_t$	-0.10			
	(0.080)			
$\ln(\text{Population})_t$	0.091			
	(0.27)			
$\Delta\ln(\text{RH lane miles})_t$		1.21***	1.19***	1.19***
		(0.061)	(0.071)	(0.070)
$\Delta\ln(\text{Subway miles})_t$		-0.072***	-0.056**	-0.084**
		(0.023)	(0.028)	(0.038)
$\Delta\ln(\text{Population})_t$		1.24***	0.85***	0.85***
		(0.13)	(0.32)	(0.33)
$\Delta\ln(\text{RH lane miles})_{t-3}$			0.0090	0.0092
			(0.052)	(0.052)
$\Delta\ln(\text{Subway miles})_{t-3}$			0.037	0.049*
			(0.027)	(0.029)
MSA FE	-	10	10	10
F statistics of first stage	2.47	40.00	64.64	-
Observations	237	232	227	227
R-squared	0.879	0.945	0.947	0.947

[1] RH refers to ring highways. Year fixed effects are included in all regressions.
[2]IV for $\ln(RH)_t$ is highway plan in year 1947. IVs for $\Delta\ln(S)_t$ and $\Delta\ln(S)_{t-3}$ are subway miles in year t-5 and year t-7.
[3]Robust standard errors in parentheses. Clustered standard errors at MSAs for (1). *** p<0.01, ** p<0.05, * p<0.1.

Table 10: ln(Vehicle miles traveled) on **Radial Highways** (1991-2014)

	(1)	(2)	(3)	(4)	(5)	(6)
	Level		3-year difference			
VARIABLES	MSA FE	MSA FE	MSA FE	IV for $\Delta\ln(S)_t$	MSA FE	IV for $\Delta\ln(S)_t$ & $\Delta\ln(S)_{t-3}$
$\ln(\text{RAH lane miles})_t$	1.32***	1.30***				
	(0.21)	(0.22)				
$\ln(\text{Subway miles})_t$	0.033	-0.051				
	(0.021)	(0.051)				
$\ln(\text{Population})_t$	-0.11	-0.25				
	(0.29)	(0.29)				
$\ln(\text{RAH lane miles})_{t-3}$		0.21				
		(0.13)				
$\ln(\text{Subway miles})_{t-3}$		0.075**				
		(0.031)				
$\Delta\ln(\text{RAH lane miles})_t$			1.29***	1.29***	1.30***	1.30***
			(0.23)	(0.21)	(0.23)	(0.21)
$\Delta\ln(\text{Subway miles})_t$			0.019	0.15**	-0.020	0.00032
			(0.035)	(0.064)	(0.041)	(0.10)
$\Delta\ln(\text{Population})_t$			0.10	0.10	0.100	0.096
			(0.17)	(0.16)	(0.17)	(0.16)
$\Delta\ln(\text{RAH lane miles})_{t-3}$					0.030	0.028
					(0.061)	(0.055)
$\Delta\ln(\text{Subway miles})_{t-3}$					0.15***	0.20**
					(0.051)	(0.090)
MSA FE	10	10	10	10	10	10
F statistics of first stage	-	-	-	39.51	-	-
Observations	237	234	234	232	231	230
R-squared	0.978	0.979	0.849	0.846	0.853	0.852

[1]RAH refers to radial highways, which are 1- or 2-digit highways that connect different MSAs. Year fixed effects are included in all regressions.

[2]Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: ln(Vehicle miles traveled) on **Non-Highway Arterial Roads** (OLS, 1991-2014)

	(1)	(2)	(3)	(4)	(5)	(6)
	Level		3-year difference			
VARIABLES	MSA FE	MSA FE	OLS	MSA FE	OLS	MSA FE
$\ln(\text{NHAR lane miles})_t$	0.89***	0.89***				
	(0.025)	(0.029)				
$\ln(\text{Subway miles})_t$	-0.12***	-0.20***				
	(0.022)	(0.045)				
$\ln(\text{Population})_t$	0.32***	0.34***				
	(0.12)	(0.13)				
$\ln(\text{NHAR lane miles})_{t-3}$		0.0026				
		(0.021)				
$\ln(\text{Subway miles})_{t-3}$		0.039				
		(0.024)				
$\Delta\ln(\text{NHAR lane miles})_t$			0.87***	0.87***	0.87***	0.87***
			(0.024)	(0.025)	(0.025)	(0.026)
$\Delta\ln(\text{Subway miles})_t$			-0.13***	-0.14***	-0.14***	-0.14***
			(0.026)	(0.030)	(0.031)	(0.033)
$\Delta\ln(\text{Population})_t$			0.066	0.051	0.064	0.047
			(0.070)	(0.077)	(0.070)	(0.079)
$\Delta\ln(\text{NHAR lane miles})_{t-3}$					-0.0046	-0.0094
					(0.011)	(0.011)
$\Delta\ln(\text{Subway miles})_{t-3}$					0.026	0.024
					(0.018)	(0.025)
MSA FE	10	10	-	10	-	10
Observations	237	234	234	234	231	231
R-squared	0.987	0.987	0.960	0.964	0.960	0.964

[1]NHAR refers to non-highway arterial roads. Year fixed effects are included in all regressions.

[2]Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 12: ln(Vehicle miles traveled) on **Non-Highway Arterial Roads** (2SLS, 1991-2014)

	(1)	(2)	(3)	(4)
	Level	3-year difference		
VARIABLES	IV for $ln(NHAR)_t$	IV for $\Delta ln(S)_t$	IV for $\Delta ln(S)_{t-3}$	IV for $\Delta ln(S)_t$ and $\Delta ln(S)_{t-3}$
$ln(\text{NHAR lane miles})_t$	-0.31			
	(0.47)			
$ln(\text{Subway miles})_t$	-0.074			
	(0.057)			
$ln(\text{Population})_t$	1.24**			
	(0.52)			
$\Delta ln(\text{NHAR lane miles})_t$		0.87***	0.87***	0.87***
		(0.024)	(0.024)	(0.024)
$\Delta ln(\text{Subway miles})_t$		-0.13***	-0.14***	-0.13**
		(0.035)	(0.041)	(0.061)
$\Delta ln(\text{Population})_t$		0.052	0.046	0.046
		(0.071)	(0.072)	(0.072)
$\Delta ln(\text{NHAR lane miles})_{t-3}$			-0.0100	-0.0099
			(0.011)	(0.010)
$\Delta ln(\text{Subway miles})_{t-3}$			0.033	0.032
			(0.036)	(0.045)
MSA FE	-	10	10	10
F statistics of first stage	7.35	38.37	57.09	-
Observations	237	232	230	230
R-squared	0.606	0.964	0.964	0.964

[1]NHAR refers to non-highway arterial roads. Year fixed effects are included in all regressions.

[2]IV for current highway lane miles is highway plan in year 1947. IVs for $\Delta ln(S)_t$ and $\Delta ln(S)_{t-3}$ are subway miles in year t-5 and year t-7.

[3]Robust standard errors in parentheses. Clustered standard errors at MSAs for (1). *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Table A1: Robustness check for using 1-year difference (1991-2014)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Subway PMT			Interstate Highway VMT		Ring highway VMT		Non-highway arterial road VMT	
	FE	FE	IV for $\Delta \ln(S)_t$	FE	FE	FE	FE	FE	FE
$\Delta \ln$(Subway miles)$_t$	0.64**	0.53*	1.20***	-0.019	-0.014	-0.049*	-0.030	-0.13***	-0.15***
	(0.32)	(0.30)	(0.45)	(0.029)	(0.036)	(0.030)	(0.034)	(0.042)	(0.049)
$\Delta \ln$(IH lane miles)$_t$	0.0079	0.028	0.027	1.16***	1.17***				
	(0.060)	(0.059)	(0.067)	(0.041)	(0.040)				
$\Delta \ln$(RH lane miles)$_t$	-0.00092	-0.0098	-0.0050			1.21***	1.21***		
	(0.033)	(0.033)	(0.032)			(0.062)	(0.063)		
$\Delta \ln$(NHAR lane miles)$_t$	-0.0067	-0.00078	-0.0070					0.86***	0.86***
	(0.022)	(0.014)	(0.024)					(0.023)	(0.023)
$\Delta \ln$(Population)$_t$	0.18	-0.12	0.25	0.74	0.61	1.70*	0.99	-0.63	-0.41
	(0.46)	(0.46)	(0.40)	(0.56)	(0.58)	(0.86)	(0.62)	(0.78)	(0.77)
$\Delta \ln$(Subway miles)$_{t-3}$		0.41*			0.064**		0.041		0.029
		(0.22)			(0.028)		(0.029)		(0.034)
$\Delta \ln$(IH lane miles)$_{t-3}$		0.18			0.033				
		(0.24)			(0.076)				
$\Delta \ln$(RH lane miles)$_{t-3}$		0.11					0.093		
		(0.27)					(0.072)		
$\Delta \ln$(NHAR lane miles)$_{t-3}$		-0.020							-0.0045
		(0.026)							(0.012)
MSA/City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
F statistics of first stage	-	-	9.36	-	-	-	-	-	-
Observations	314	272	276	236	233	236	232	236	233
R-squared	0.315	0.305	0.276	0.940	0.941	0.952	0.970	0.975	0.976

[1]IV for $\Delta \ln(S)_t$ is whether the city has a representative on transportation committee of Congress 7 years ago. Year fixed effects are included in all regressions.
[2] IH denotes interstate highways. RH refers to ring highways. NHAR annotates non-highway arterial roads.
[3] Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Robustness check for using **5-year difference** (1991-2014)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Subway PMT			Interstate Highway VMT		Ring highway VMT		Non-highway arterial road VMT	
	FE	FE	IV for $\Delta\ln(S)_t$	FE	FE	FE	FE	FE	FE
$\Delta\ln(\text{Subway miles})_t$	1.20***	0.93***	1.19***	-0.0069	-0.024	-0.094***	-0.059	-0.12***	-0.19***
	(0.088)	(0.15)	(0.21)	(0.019)	(0.041)	(0.018)	(0.042)	(0.024)	(0.043)
$\Delta\ln(\text{IH lane miles})_t$	0.083	0.14	0.081	1.00***	1.00***				
	(0.12)	(0.096)	(0.11)	(0.089)	(0.092)				
$\Delta\ln(\text{RH lane miles})_t$	-0.12	-0.14**	-0.12*			1.21***	1.18***		
	(0.075)	(0.062)	(0.070)			(0.051)	(0.060)		
$\Delta\ln(\text{NHAR lane miles})_t$	-0.012	0.053	-0.010					0.85***	0.85***
	(0.038)	(0.038)	(0.046)					(0.019)	(0.019)
$\Delta\ln(\text{Population})_t$	0.71	0.099	0.71*	0.27***	0.28***	1.32***	0.89**	0.067	0.036
	(0.44)	(0.55)	(0.41)	(0.063)	(0.080)	(0.24)	(0.36)	(0.044)	(0.044)
$\Delta\ln(\text{Subway miles})_{t-3}$		0.51***			0.059**		0.0063		0.086**
		(0.098)			(0.027)		(0.033)		(0.035)
$\Delta\ln(\text{IH lane miles})_{t-3}$		-0.048			-0.035				
		(0.28)			(0.065)				
$\Delta\ln(\text{RH lane miles})_{t-3}$		0.16					0.0086		
		(0.34)					(0.059)		
$\Delta\ln(\text{NHAR lane miles})_{t-3}$		-0.011							-0.016
		(0.037)							(0.011)
MSA/City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
F statistics of first stage	-	-	18.74	-	-	-	-	-	-
Observations	258	216	258	232	228	230	224	232	228
R-squared	0.738	0.698	0.738	0.907	0.909	0.934	0.939	0.968	0.969

[1]IV for $\Delta\ln(S)_t$ is whether the city has a representative on transportation committee of Congress 7 years ago. Year fixed effects are included in all regressions.
[2] IH denotes interstate highways. RH refers to ring highways. NHAR annotates non-highway arterial roads.
[3] Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Δln(Passenger miles travelled) of Subways (**MSA level**, 1991-2014)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	FE	FE	IV1	IV2	Both IVs	Both IVs
Δln(Subway miles)$_t$	0.92***	0.90***	1.05***	1.15***	1.15***	0.96***
	(0.15)	(0.13)	(0.32)	(0.23)	(0.23)	(0.16)
Δln(IH lane miles)$_t$	-0.016	0.058	-0.14	-0.12	-0.12	0.021
	(0.10)	(0.10)	(0.10)	(0.090)	(0.090)	(0.080)
Δln(RH lane miles)$_t$	-0.074	-0.078	-0.0057	0.019	0.019	-0.072
	(0.061)	(0.076)	(0.064)	(0.061)	(0.060)	(0.052)
Δln(NHAR lane miles)$_t$	0.023	-0.0016	0.083	0.034	0.034	0.059*
	(0.047)	(0.037)	(0.082)	(0.054)	(0.054)	(0.036)
Δln(MSA population)$_t$	0.35***	1.64**	2.91***	3.20***	3.20***	1.83***
	(0.084)	(0.79)	(0.88)	(0.72)	(0.72)	(0.68)
Δln(Subway miles)$_{t-3}$		0.52***				0.49***
		(0.19)				(0.18)
Δln(IH lane miles)$_{t-3}$		-0.012				0.37**
		(0.13)				(0.18)
Δln(RH lane miles)$_{t-3}$		-0.046				-0.12
		(0.095)				(0.20)
Δln(NHAR lane miles)$_{t-3}$		-0.030				-0.043**
		(0.025)				(0.020)
MSA FE	10	10	10	10	10	10
F statistics of first stage	-	-	3.36	46.50	30.41	69.18
Over-identification test	-	-	-	-	0.88	0.54
Observations	234	228	189	187	187	186
R-squared	0.629	0.653	0.683	0.635	0.635	0.719

[1]IV1 is transportation committee assignment 7 years ago. IV2 is subway miles 5 years ago. Year fixed effects are included in all regressions.
[2] IH denotes interstate highways. RH refers to ring highways. NHAR annotates non-highway arterial roads.
[3]Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Robustness check of using **4-year lag** (1991-2014)

	(1)	(2)	(3)	(4)
VARIABLES	Subway PMT	Interstate Highway VMT	Ring Highway VMT	Non-highway Arterial road VMT
Δln(Subway miles)$_t$	1.32***	-0.018	-0.042	-0.12***
	(0.26)	(0.036)	(0.027)	(0.045)
Δln(IH lane miles)$_t$	0.018	1.09***		
	(0.094)	(0.059)		
Δln(RH lane miles)$_t$	-0.12*		1.19***	
	(0.059)		(0.077)	
Δln(NHAR lane miles)$_t$	0.087**			0.87***
	(0.035)			(0.026)
Δln(Population)$_t$	0.69	0.18	0.82**	0.047
	(0.43)	(0.21)	(0.36)	(0.079)
Δln(Subway miles)$_{t-4}$	0.26*	0.051	0.035*	0.015
	(0.15)	(0.036)	(0.019)	(0.025)
Δln(IH lane miles)$_{t-4}$	-0.091	-0.0032		
	(0.26)	(0.051)		
Δln(RH lane miles)$_{t-4}$	0.19		-0.033	
	(0.33)		(0.035)	
Δln(NHAR lane miles)$_{t-4}$	-0.056			-0.0071
	(0.038)			(0.0093)
MSA/City FE	Y	Y	Y	Y
Observations	230	230	226	230
R-squared	0.535	0.885	0.951	0.964

[1] IH denotes interstate highways. RH refers to ring highways. NHAR annotates non-highway arterial roads. Year fixed effects are included in all regressions.
[2] Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Δln(Passenger miles traveled) of **Rail and Bus** (1991-2014)

	(1)	(2)	(3)	(4)
	Δln(PMT) for rail		Δln(PMT) for bus	
VARIABLES	FE	IV for $\Delta\ln(R)_t$	FE	IV for $\Delta\ln(B)_t$
$\Delta\ln(\text{Rail miles})_t$	1.02***	1.40***	-0.067***	-0.098***
	(0.19)	(0.16)	(0.023)	(0.032)
$\Delta\ln(\text{Number of bus})_t$	0.26*	0.31**	0.88***	1.08***
	(0.15)	(0.15)	(0.093)	(0.11)
$\Delta\ln(\text{Subway miles})_t$	0.032	0.031	-0.092**	-0.081*
	(0.077)	(0.065)	(0.042)	(0.043)
$\Delta\ln(\text{Population})_t$	4.05***	3.98***	0.17	0.039
	(0.98)	(0.98)	(0.18)	(0.17)
City FE	38	38	394	394
F statistics for first stage	-	13.02	-	52.97
Observations	470	470	5,275	4,561
R-squared	0.615	0.579	0.303	0.281

[1] $\Delta\ln(R)_t$ refers to $\Delta\ln(\text{Rail miles})_t$. Rail includes light rail and commuter rail. $\Delta\ln(B)_t$ denotes $\Delta\ln(\text{Number of bus})_t$. Year fixed effects are included in all regressions. All differences are 3-year difference.

[2] IV for $\Delta\ln(R)_t$ is rail miles 3 years ago. IV for $\Delta\ln(B)_t$ is number of buses 5 years ago.

[3] Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

References

Anderson, M. L. (2014). Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion. *American Economic Review*, *104*(9), 2763-96.

Baum-Snow, N. (2007). Did highways cause suburbanization?. *The Quarterly Journal of Economics*, *122*(2), 775-805.

Baum-Snow, N., Brandt, L., Henderson, J. V., Turner, M. A., & Zhang, Q. (2017). Roads, railroads, and decentralization of Chinese cities. *Review of Economics and Statistics*, *99*(3), 435-448.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, *90*(3), 414-427.

Cervero, R. (2002). Induced travel demand: Research design, empirical evidence, and normative policies. *Journal of Planning Literature*, *17*(1), 3-20.

Downs, A. (1962). The law of peak-hour expressway congestion. *Traffic Quarterly*, *16*(3).

Duranton, G., & Turner, M. A. (2011). The fundamental law of road congestion: Evidence from US cities. *American Economic Review*, *101*(6), 2616-52.

Duranton, G., & Turner, M. A. (2012). Urban growth and transportation. *Review of Economic Studies*, *79*(4), 1407-1440.

Gendron-Carrier, N., Gonzalez-Navarro, M., Polloni, S., & Turner, M. A. (2017). *Subways and urban air pollution* (No. w24183). National Bureau of Economic Research.

Gonzalez-Navarro, M., & Turner, M. A. (2016). Subways and urban growth: evidence from earth.

Goodwin, P. B. (1996). Empirical evidence on induced traffic. *Transportation*, *23*(1), 35-54.

Holden, D. J. (1989). Wardrop's third principle: urban traffic congestion and traffic policy. *Journal of Transport Economics and Policy*, 239-262.

Hsu, W. T., & Zhang, H. (2014). The fundamental law of highway congestion revisited: Evidence from national expressways in Japan. *Journal of Urban Economics*, *81*, 65-76.

Knight, B. (2005). Estimating the value of proposal power. *American Economic Review*, *95*(5), 1639-1652.

Knight, B. (2002). Endogenous federal grants and crowd-out of state government spending: Theory and evidence from the federal highway aid program. *American Economic Review*, *92*(1), 71-92.

Litman, T. (2015). *Evaluating public transit benefits and costs*. British Columbia, Canada: Victoria Transport Policy Institute.

Nelson, P., Baglino, A., Harrington, W., Safirova, E., & Lipman, A. (2007). Transit in Washington, DC: Current benefits and optimal level of provision. *Journal of urban Economics*, *62*(2), 231-251.

Pang, J. (2017). Do subways improve labor market outcomes for low-skilled workers?

Parry, I. W., & Small, K. A. (2009). Should urban transit subsidies be reduced?. *American Economic Review*, *99*(3), 700-724.

Schrank, D., Eisele, B., Lomax, T., & Bak, J. (2015). 2015 urban mobility scorecard.

Stewart, C. III & Woon J. (2016). Congressional Committee Assignments, 103rd to 114th Congresses, 1993--2017: House, 2016.

Stopher, P. R. (2004). Reducing road congestion: a reality check. *Transport Policy*, *11*(2), 117-131.

United States Department of Energy. (2012). Transportation Energy Data Book: Edition 30. *Oak Ridge Tennessee: Oak Ridge National Laboratory.*

Winston, C., & Maheshri, V. (2007). On the social desirability of urban rail transit systems. *Journal of urban economics*, *62*(2), 362-382.

VITA

NAME OF AUTHOR: Jindong Pang

Email: jipang@syr.edu

Website: https://jipang.expressions.syr.edu/

EDUCATION:

2011 B.S. Xi'an Jiaotong University, Shaanxi, China

2013 M.S. Xi'an Jiaotong University, Shaanxi, China

RESEARCH EXPERIENCE AND EMPLOYMENT:

2014 – 2018 Teaching Assistant, Department of Economics, Syracuse University

2015 – 2018 Research Associate, Center for Policy Research, Syracuse University

AWARDS AND HONORS:

2014 – 2018 Syracuse University Graduate Assistantship, Syracuse University

2009 National Scholarship, Xi'an Jiaotong University

2008 National Scholarship, Xi'an Jiaotong University