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Lunyu Xie

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Central America
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Tropical Agricultural Research and Higher Education Center (CATIE)
Email: efd@catie.ac.cr

China
Environmental Economics Program in China (EEPC)
Peking University
Email: EEPC@pku.edu.cn

Ethiopia
Environmental Economics Policy Forum for Ethiopia (EEPFE)
Ethiopian Development Research Institute (EDRI/AAU)
Email: eepfe@ethionet.et

Kenya
Environment for Development Kenya
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University of Nairobi
Email: kenya@efdinitiative.org

South Africa
Environmental Economics Policy Research Unit (EPRU)
University of Cape Town
Email: southafrica@efdinitiative.org

Tanzania
Environment for Development Tanzania
University of Dar es Salaam
Email: tanzania@efdinitiative.org

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Abstract

Using individual travel diary data collected before and after the rail transit coverage expansion in urban Beijing, this paper estimates the impact of rail accessibility improvement on the usage of rail transit, automobiles, buses, walking, and bicycling, measured as percent distance traveled by each mode in an individual trip. My results indicate that the average rail transit usage significantly increased, by 98.3% for commuters residing in the zones where the distances to the nearest station decreased because of the expansion, relative to commuters in the zones where the distances did not change. I also find that auto usage significantly decreased, by 19.8%, while the impact on bus usage was small and not statistically significant. Average walking and bicycling distance (combined) increased by 11.8%, indicating that walking and bicycling are complements to urban rail transit, instead of substitutes. Furthermore, I find that estimated changes in auto usage and rail transit usage vary significantly with auto ownership and income.

Key Words: travel mode, urban rail transit, traffic diversion, travel diary data

JEL Classifications: D12, H43, H54, Q53, R22, R41, R42

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Introduction

Many metropolitan areas world-wide are investing heavily in building or extending urban rail transit systems,[1] aiming to reduce road congestion and air pollution caused by the wide use of automobiles.[2] Whether these goals can be met depends on which travel modes commuters reduce when they substitute more rail transit. This remains an open question in practice. This study investigates this topic in the context of Beijing, a mega-city unique in the speed of its subway development. With a $30 billion[3] investment in building new subway lines, Beijing's subway system has grown from two small initial lines with 41 stations to a system with more than 400 stations in only eight years.[4] The rollout of new subway lines creates a series of contrasts between commuters who experienced rail accessibility improvements and those who did not. In this paper, I take advantage of this rollout to estimate, *ex post*, how the completion of new rail transit lines affected kilometers traveled by rail transit, autos, buses, and walking and bicycling, respectively.

Investment in commuter rail transit is a world-wide phenomenon, driven by the belief in its benefits, such as less congestion, less air pollution, improved labor market access for the poor,

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* Ph.D. candidate, Department of Agricultural and Resource Economics, University of California, Berkeley. Email: xielunyu@berkeley.edu. I am grateful to Peter Berck, Sofia Berto Villas-Boas, and Jintao Xu for their invaluable advice, and to Michael Anderson, Maximilian Auffhammer, Jing Cai, Meredith Fowlie, Yizhen Gu, Alain de Janvry, Jeremy Magruder, Dave Rapson, Elisabeth Sadoulet, Wolfram Schlenker, Qu Tang, Christian Traeger, and seminar participants at UC Berkeley and EfD annual meetings for many helpful comments. I also thank the Beijing Transportation Research Center for providing the household travel diary data for this study. The latest version of this paper is available at: http://areweb.berkeley.edu/candidate/lunyu_xie.

[1] According to the International Association of Public Transport, since the beginning of 2012, 37 cities opened or extended metro systems, tram and light rail systems. 155 million passengers per day in over 116 cities in Europe, North America, South America, Asia, and the Middle East and North Africa were carried by urban rail transit in 2006, and the number is growing.

[2] According to Parry and Small (2009), the cost of local and global air pollution, congestion, and accidents varies from $ .46 per mile for Washington DC to $2.42 per mile for London.

[3] 200 billion Chinese Yuan.

[4] The rapid expansion of Beijing's urban rail transit system started in 2007. The construction plan is to have a rail system of 700 kilometers by 2015. More details of the Beijing subway expansion history and plan are provided in the next section.

and higher productivity in industries that make substantial use of vehicles in their production processes (Kain 1968, Vickrey 1969, Fernald 1999, Chen and Whalley 2012). Transit authorities believe that the benefit is large; hence, the investment in rail transit is large (Cervero, 1998). For the same reason, passenger fares for public transportation are usually heavily subsidized (Kenworthy and Laube 2001, Parry and Small 2009). However, some researchers argue that the cost to build and maintain new transit is higher than the measured benefit, and point out that the optimistic view of the rail transit benefit was based partially on an overestimation of ridership (Gorden and Willson 1984, Allport and Thomson 1990, Kain 1991, Kain 1992, Pickrell 1992 , Kain 1997a). Besides the unsettled question concerning rail ridership, another question not well addressed in previous literature is from which alternative travel modes rail transit riders are diverted. The rail benefit will be higher if rail transit ridership comes at the expense of more polluting modes such as automobiles, rather than less polluting modes such as bicycles. This study addresses the two questions simultaneously by looking into the changes in distance traveled by various modes.

It is of particular interest to study the effect of rail transit on mode usage in a city in the developing world, because the rapid increase in auto use that goes along with economic growth in developing countries is causing both local and global problems. As pointed out by Wolfram et al. (2012), an increase in income for the poor leads to an increase in the purchase of energy-using assets. The exponential increase in auto ownership in the past decade in China is one example. Auto ownership increased from 4 million to 5 million in Beijing in 2010, before the implementation of the license plate lottery.[5] The rapid increase in auto usage has brought great challenges to road capacity and air quality. According to the Beijing Transportation Commission, the space taken by autos exceeds the sum of all road spaces and parking lot spaces in urban Beijing; the average speed during rush hours is less than 20 kilometers per hour; and more than 50% of the airborne pollution comes from auto exhaust. Transportation sectors also significantly contribute to greenhouse gases, given the large population in Beijing and other major cities in developing countries. If the rail transit being constructed in the developing world slows down the rapid increase in auto use, it will benefit not only the local residents, but also the rest of the world, which is affected by greenhouse gas emissions. However, the literature on urban rail

[5] The license plate lottery, starting in January 2011, restricts car ownership. Only the winners of the lottery are allowed to register license plates for new cars. Each month, 20,000 new plates are issued.

transit's effect on mode use in developing countries is sparse, because heavy auto use is recent and urban rail transit is still very limited.

This paper is the first study to use a (pseudo) panel of individual trips to estimate the *ex post* effect of rail transit provision on mode usage, measured as the percent distance traveled in a mode, in the context of a city in the developing world. Taking advantage of three rounds of detailed individual travel dairies in Beijing, with new subway lines completed between the rounds, I observe households before and after the coverage changes. I also observe households that are affected and those that are not affected. This is possible because the rail expansion improved accessibility for the households residing along the new lines, while not for the rest. In other words, a counterfactual is provided by commuters in zones where the distances between their area of residence and the rail station remained the same. The main estimation strategy is the differences-in-differences (DID) method. With the unique dataset and the double comparison estimation strategy, I am able to alleviate several identification problems present in most previous literature.

First, the double differencing removes two types of biases (Imbens and Wooldridge 2009). One bias comes from the comparison between the treatment group and the control group that could be the result of permanent differences between these groups. People who prefer rail transit tend to choose to live in areas near rail stations. Cross-sectional studies (Gordon and Willson 1984, Wardman 1997, Winton and Shirley 1998, Petitte 2001, Kain and Liu 2002) comparing commuters in nearby areas to those in further areas usually suffer from this self-selection bias. The other bias comes from the comparison over time that could be the result of time trends unrelated to the treatment. Macroeconomic shocks and transport policies[6] can be the sources of such bias, from which time-series studies (Gaudry 1975, Greene 1992, Gomez-Ibanze 1996) tend to suffer.

Second, the estimation of *ex post* effect is preferred in terms of causal inference, given the difficulty in predicting the market share of a new rail system by an *ex ante* study (MacFadden

[6] The Beijing municipal government adopted a series of measures in last five years aiming to reduce auto use. The low fare public transit policy, adopted in 2007, discounts bus fare up to 80% and decreases subway fares from 3-5 yuan to a single price of 2 yuan. A driving restriction in effect from July 20 to September 20, 2008 (for the Olympic Games in Beijing) banned half of automobiles from the roads by the last digit of a license plate (even digit for even dates, odd digit for odd dates). A relaxed driving restriction, in effect since October 11, 2008, banned 20 percent of automobiles. A license plate lottery, starting in January 2011, restricts auto ownership. Parking fees in the urban area increased by up to five times the previous rates, starting in April 2011.

and Talvitie 1977). Discrete choice models,[7] widely used in the travel mode choice literature, require accurately constructing attribute of alternatives, especially the alternative specific constants. Inaccurate construction of the alternatives tends to result in inaccurate prediction. Despite the effort put into McFadden's pioneering work (McFadden and Talvitie 1977) to project ridership for the Bay Area Rapid Transit (BART) system in the San Francisco Bay Area, the projected transit share is still 37% larger than the actual transit share (Train 1978).

Third, this study takes advantage of the relatively high frequency of the annually repeated observations, compared to that of census data with observations every 10 years. The frequency of the data reduces the endogeneity problem caused by the individual's joint decision: whether to own an auto and how much to drive it. The data frequency also addresses the self-selection bias caused by migration. Baum-Snow and Kahn (2000) used aggregate data at the census tract level with data points ten years apart, so they accounted for migration with a predetermined migration rate. While I build upon their research design, this paper uses very different data, and the short time frame (annually repeated individual observations) limits the bias caused by migration. I test these two potential endogeneities in a later section.

Finally, the rich information from individual travel diary data allows me to define a continuous dependent variable, which usually has not been possible in previous studies with individual data.[8] The dependent variable in this paper is defined as the percent distance traveled by each mode in an individual trip, which is continuous between 0 and 1. This continuous definition has two advantages. First, it avoids the arbitrary definition of the main mode when a trip involves more than one mode, which is almost always the case in practice. Second, a continuous definition reflects not only the change in the main mode, but also the change in the mode composition. Without the detailed information on mode composition, I would not have

[7] An incomplete list for ex ante studies on travel mode by discrete choice models: Ben-Akiva and Lerman 1974, McFadden 1974, Train 1978, Train 1980, Ben-Akiva and Morikawa 1990, Hensher and Brandley 1993, Hensher 1994, Ortuza and Iacobelli 1998, Bhat 2000, Asensio 2002, Alpizar and Carlsson 2003, Carlsson 2003, Hensher and Rose 2007, and Liu 2007.

[8] For aggregate data, the mode usage is measured as the ridership of a transit line or the market share of a mode. They are naturally continuous. For individual data, the natural choice is also continuous, as nearly every transit trip is a mixture of modes. For instance, a trip mostly on subway may also include a bus, walking or bicycling as part of the journey. However, standard survey data do not have this detailed information, because in questionnaires it is natural to ask about the modes or the mode combinations the commuter uses, instead of the distance for each mode involved in a trip. Therefore, it is common in the literature to choose discrete models, at the cost of losing information.

found the impact of the subway expansion on the walking and bicycling share in a trip, because walking and bicycling are not likely substitutes for the subway as a main mode.

My results indicate that the rail transit usage of commuters who experienced the improvement in rail transit accessibility, measured as the distance between home and the nearest subway station, increased by 98.3%, on average, relative to the commuters who did not experience such improvement. Automobile usage decreased by 19.8%. Bus usage fell by 5%; that decrease is not statistically significant. The diversion of commuters from autos to rail lines caused an increase in walking and bicycling of 11.8%, showing that walking and bicycling are complements to rail transit, instead of substitutes. These results are robust to alternative definitions of mode usage and specifications. Furthermore, I find that drivers (as opposed to riders) and commuters with higher income are less likely to switch from automobile to rail transit. Because I use percent of distance traveled, I also examine the effect of transit expansion on the number of trips. I find that neither the number of commute work trips nor their length increased, indicating that the quantity of travel is not increased by the subway expansion.

The reminder of the paper is organized as follows. The next section provides background on the urban rail transit expansion in Beijing. The section that follows summarizes the data and the graphic results. Next, I describe the empirical estimation strategy and present the results. The last section concludes.

Urban Rail Transit in Beijing

Beijing had only two subway lines for more than 30 years, until the rapid expansion in the last five years. The first two subway lines (Line 1 and Line 2) started operation in 1969. Another two lines (Line 13 and Line Batong) were added in 2002 and 2003, respectively. After being selected to host the 2008 Olympics, Beijing invested heavily in building new subway lines. The subway system expanded from 114 kilometers in 2003 to 371 kilometers in 2011.The number of stations increased from 70 to 219. According to the Beijing Rail Transit 2015 Plan by the Beijing Municipal Commission of Urban Planning, the total investment will be over $30 billion for a subway system of 704 kilometers with 421 stations by 2015. [9] All residents in urban Beijing will be within a 30-minute walking distance of at least one subway station.

New subway lines were opened every year since 2007. Line 5, opened in October 2007, goes north and south. It runs 28 kilometers and has 23 stations. Line 8 and Line 10, opened in July 2008, go from west to east and then turn south. They run 40 kilometers and have 26 stations. Line 4, opened in September 2009, goes northwest and south. After 2009, Line 8 was expanded to the north, and six lines (Line 15, Line Changping, Line Daxing, Line Fangshan, Line Yizhuang, and Line 9) were added at four corners and the south of the system. The subway expansion history and 2015 Plan are shown in Figure 1.

The subway lines studied in this paper are Line 5, Line 8, and Line 10. There are two reasons why they are of particular interest. One reason is that these three lines go in different directions and cover wide areas which are geographically representative. Beijing's development is based on the expansion of ring roads, all centered at Tiananmen Square. Residential areas within the inner rings tend to be wealthier. As shown in Figure 2, Line 5, 8, and 10 cut vertically and horizontally across several rings. Therefore, the areas covered by these three lines are representative of different income levels. The other reason is that these three lines operate mainly within urban Beijing, an area that is highly populated[10] and developed. Restricted by the land available for new housing projects, the migration rate in this area is relatively low. Therefore the self-selective bias is limited. This hypothesis is tested indirectly in a later section.

Data and Graphical Results

Data

This study uses travel diary data from 2007, 2008, and 2009,[11] covering periods before and after the opening of Line 5, Line 8, and Line 10, as shown in Figure 1. The travel diary data

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[9] This investment is greater than all rail transit investments in 16 major U.S. metropolitan areas over 30 years. According to Baum-Snow and Kahn (2005), $25 billion from federal, state, and local governments was spent in establishing or expanding rail transit infrastructure between 1970 and 2000 for Atlanta, Baltimore, Boston, Buffalo, Chicago, Dallas, Denver, Los Angeles, Miami, Portland, Sacramento, San Diego, San Francisco, San Jose, and St. Louis, and Washington.

[10] According to 2010 census data, the population density in urban Beijing is greater than 5000 people per square kilometer.

[11] The interviews were held on weekdays from May 20 to June 11 in 2007, May 13 to June 5 in 2008, and June 12 to 26 in 2009. Line 5 started operation on October 7, 2007. Line 8 and 10 started operation on July 19, 2008.

are from the Beijing Household Travel Survey (BHTS) done by the Beijing Transportation Commission (BTC) every year since the 1980s. In each of the eight urban districts,[12] households are randomly selected, stratified by Traffic Analysis Zone (TAZ). TAZs are geocoded areas, divided by the BTC for the purpose of traffic analysis. Each administrative district has 16 to 238 TAZs, based on the size of the area and the population of a district. In each TAZ, about 25 households are randomly selected for interviews in person to collect data on trips taken during a designated 24-hour period (the household's travel day). Table 1 lists the number of TAZs and households surveyed each year. The sampling strategies are consistent from 2007 through 2009, although fewer TAZs are surveyed in 2008 and 2009. In this paper, I restrict the sample to the 71 TAZs that are surveyed in all three years, which I refer as the TAZ panel. As shown in Figure 3, the TAZs in the panel are scattered mostly within or close to the 5th ring road[13] and are geographically representative.

The survey gathers: (1) information about each segment of a trip taken during the household's travel day, including travel purpose (e.g. going to work, shopping, transferring[14]), travel mode (e.g., auto, bus, subway), travel distance, time when the travel began and ended, and TAZ code of the origin and the destination; (2) household information, including TAZ code of the residence, vehicle ownership, and monthly household income (level 1-8); (3) household member information, including gender, age, occupation, possession of a driver's license, and the TAZ code of the school (if a student) or the place of work (if an employee). I aggregate 14 modes in the surveys into four broader categories: (1) subway, (2) bus (including regular bus, minibus, and shuttle), (3) auto (including driving a private auto, riding in a private auto, driving a company auto, riding in a company auto, and taxi), and (4) walking and bicycling.

To measure the improvement in rail transit accessibility, I calculate each TAZ's proximity to rail transit in 2007, 2008, and 2009, using digital maps of TAZs and subway stations. The map of TAZs is taken from BTC. The map of transit stations is taken from the

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[12] A small portion of TAZs outside the urban districts were selected. In this paper, I exclude households in those TAZs.

[13] It is called the "5th ring road," but it is actually the fourth ring rode if counted from the innermost one. There is no "1st ring road." The innermost one is called the "2nd ring road."

[14] Transferring means switching modes. It can be the purpose of a trip segment, but not the purpose of a trip. In this paper, I define a trip as traveling between two places with a specific purpose, excluding going to subway/bus stations, taking a taxi, transferring, and parking. Only one mode is involved in one segment of a trip, although a trip can have more than one mode.

OpenStreetMap database prepared by GEOFABRIK. Based on this database, the rail transit coverage for 2007, 2008, and 2009 is constructed using separate transit histories taken from the official announcements of the operation of new lines. TAZs' centroids and their distances to the nearest rail station in each year are calculated using a near-distance script that is available in the ArcGIS software package. All households from the same TAZ are treated as residing at the same point.15 This approximation is acceptable, because TAZs in urban Beijing are small. The average area of a TAZ is less than 1.5 square kilometers.

A TAZ is defined as "treated" if its distance to the nearest subway station decreased in 2008 (after the opening of Line 5) or 2009 (after the opening of Line 8 and Line 10). All treated TAZs are referred as the treatment group, while all untreated TAZs are the control group. There are 31 and 40 TAZs in the two groups, respectively. In the treatment group, 19 TAZs are treated after the first round of surveys, while the other 12 TAZs are not treated until after the first two rounds of surveys. I refer the 19 TAZs as the early treatment group, while the 12 TAZs are the late treatment group. As shown in Figure 4, the treated TAZs are not necessarily along new subway lines, nor are the untreated TAZs far from subway stations. In 2007, the pre-treatment period, the two groups had the same range of distances, as shown in Panel A of Figure 5. I will utilize the distance distributions to test the magnitude of self-selective migration in a later section. Panel B of Figure 5 shows the distance distribution of the treatment group in each year. The average distance fell by 1.39 kilometers (from 3.35 kilometers to 1.96 kilometers) from 2007 to 2008, and fell by 0.57 kilometers (from 1.96 kilometers to 1.39 kilometers) from 2008 to 2009. The distance reduction varied across TAZs. Some TAZs that were not within walking distance of a station ended up within walking distance. Other TAZs were within walking distance before the treatment and ended up even closer. The rest of the TAZs ended up closer but still beyond walking distance. I will discuss the heterogeneous treatment levels later.

The mode usage of a trip is measured as the percent distance traveled using that mode. Therefore, the mode usage of a trip is characterized by four continuous variables (percent distance by subway, auto, bus, and walking and bicycling), rather than being assigned into a dominant mode. As shown in Table 2, the average percent distance in work trips traveled by auto is around 30%, which is the second largest, next to the distance by walking and bicycling.

[15] This is the only way to locate a household in the survey. Due to the confidentiality requirements for human subjects, all information that can identify a household or a person, such as names and home addresses, is removed from the dataset.

Although subway usage is a small share in work trips, the share increased from year to year in the treatment group.

I focus on work trips, defined to include going to work and going to school, for two reasons. First, most road congestion happens during rush hours. Second, decisions about the destination and the travel mode are usually made jointly, especially for trips for which the destinations are easy to change, such as shopping trips. It takes much longer to change the place of work or school. Therefore, I isolate the mode choice from the destination choice by restricting the sample to work trips. This hypothesis is tested in a later section.

In additional to the mode usage of a work trip, the number of work trips and the trip distance are also of interest. One way to measure trip distance is to add up the reported distances of the trip segments. The reported distance is affected by the choices of routes and travel modes. For the same pair of origin and destination, a bus trip tends to cover a longer distance than an auto trip. To avoid this confounding factor, I also measure the point to point distance between the centroids of the origin and destination TAZs, using ArcGIS. For all trips traveling within a TAZ, the ArcGIS measured trip distance is zero.

Mode usage is influenced by factors in addition to accessibility to rail transit. These factors include commuters' socioeconomic characteristics, such as income, vehicle ownership, possession of a driver's license, gender, age, and occupation. Table 2 provides summary statistics of the mode usage for work trips, number of trips, trip distance, and demographic variables by group in 2007, 2008, and 2009.

The Impact of the Urban Rail Transit Expansion on Mode Usage

Prior to the discussion of the econometric model, some qualitative evidence can be seen from graphs comparing the mode usage trajectories between the treatment group and the control group. In the four panels of Figure 6, the average percent distance traveled by subway, auto, bus, and walking and bicycling in work trips of the treatment group is compared to that of the control group year by year. All surveyed commuters with work trips in the 31 untreated TAZs are included in the treatment group. There are two treatments, the opening of Line 5 in October 2007 and the opening of Line 8 and Line 10 in July 2008. The vertical lines show treatment dates relative to observation dates. Some TAZs are treated after the first round of surveys (early treatment group), while some others are treated after the second round of surveys (late treatment group). All surveyed commuters with work trips in the 40 untreated TAZs are included in the control group. The percent distance traveled by subway increased in both years for the treatment group after the expansion, while it remained stable in the control group. The auto travel distance of the treatment group decreased after the expansion, while it increased in the control group. For bus distance, no obvious difference is found between the two groups. Distance by walking and bicycling increased and then decreased in the treatment group, while it decreased in both years in the control group. Therefore, relative to the control group, the average usage of subway and walking and bicycling in the treatment group increased after the treatments; the average auto usage decreased; and the average bus usage did not change.

To interpret the above finding as causal effects, one key assumption is that the two groups have similar usage trajectories over time periods absent any treatment effect. This assumption is not observable and therefore not testable in principle. One possible way to assess the plausibility of this assumption is to test whether the two groups have similar usage trajectories before the treatment. Due to data availability, the full sample is observed only once before the treatments. Therefore, I compare the pre-treatment trajectories of the late treatment group, instead of the full treatment group, to those of the control group. As shown in Figure 7, the mode usage trajectories of the two groups were similar before the treatment, except for walking and bicycling. Average percent distance by walking and bicycling was stable in the late treatment group, while it decreased by 0.03 in the control group from 2007 to 2008. However, the difference is not statistically significant (t-statistics = 0.4968). In the empirical estimation section, I will confirm this pre-treatment trajectory similarity by formal econometric models.

The graphic analysis does not account for important determinants of mode usage, such as auto ownership and income. Therefore, I examine the balance of the treatment group and the control group on the covariates. I test the mean differences of income, auto ownership, gender, and age between the two groups in each year. None of them are statistically significant. This indicates that the differences in the mode usage trajectories between these two groups do not come from the differences of the demographic dynamics in the sample.

Estimation Strategies and Results

In this section, I first employ a formal econometric model to estimate the effect of the subway expansion on percent distance traveled by subway, bus, auto, and walking and bicycling. Next, I test the plausibility of some key assumptions. I also investigate the treatment effect heterogeneity. Finally, I test whether the subway expansion induced more trips.

Estimation of the Subway Expansion Effect

I am primarily interested in estimating the sample average treatment effect on the treated (SATT) for each mode m by the differences-in-differences (DID) estimator:

$$\alpha_{TT}^{m} = (\bar{Y}_{11}^{m} - \bar{Y}_{10}^{m}) - (\bar{Y}_{01}^{m} - \bar{Y}_{00}^{m}) \quad (1)$$

where $\bar{Y}_{st}^{m} = \frac{1}{\mathrm{N_{st}}}\sum_{\mathrm{i}} Y_{ist}^{m}$; s equals 1 for the treatment group, and 0 for the control group; t equals 0 when the observation is before the treatment, and 1 after the treatment. Y_{ist}^{m} is the percent distance traveled in mode m by commuter i in group s at time t.

The simplest estimate of α_{TT}^{m} is obtained by computing an unconditional DID. This estimator will be biased if factors that are related to individual travel behavior vary significantly across the treated and control groups at the same time as the treatment. In order to reduce the bias potentially introduced by observable differences across residents in the treatment group and the control group, I employ regression-based conditioning strategy. With multiple time periods (3 years, including 30 survey dates) and multiple groups (71 TAZs), I use a natural extension of the two-group-two-time-period model for the outcome in the absence of the treatment (Imbens and Wooldridge 2009). I estimate the following specification:

$$Y_{izdt}^{m} = \alpha + \boldsymbol{\beta}'\boldsymbol{X_{it}} + \tau D_{zt} + c_z + \eta_t + \varphi_{dt} + \nu_{izdt} \quad (2)$$

where Y_{izdt}^{m} is the percent distance traveled in mode m by commuter i residing in TAZ z at district d and observed at time t; $\boldsymbol{X_{it}}$ is a vector of observable covariates for commuter i observed at time t; D_{zt} is the treatment indicator, which equals 1 if TAZ z is treated at time t, 0 otherwise; c_z are TAZ dummies; η_t are time dummies; φ_{dt} are district by year dummies, and ν_{izdt} is the residual. The parameter τ captures the average effect of the subway expansion on changes in individual-level travel mode usage over time, conditional on variables in $\boldsymbol{X}$.

Results are listed in Table 3. In column (1), the basic specification, I regress mode usage on the treatment indicator, the group indicator, and year dummies. The group indicator equals 1 if the commuter is residing in a treated TAZ, 0 otherwise. In column (2), I use TAZ dummies and survey date dummies, which are finer dummies than the group indicator and the year dummies. TAZ dummies allow TAZs in the same group to have different fixed effects. Survey date dummies catch daily common shocks, such as weather. In the following columns, I add in demographic variables that are related to mode usage. Automobile ownership is an important predictor for auto usage. However, extra caution should be exercised when including auto ownership in $\boldsymbol{X}$, because it is also influenced by the treatment. When subway accessibility is improved, auto ownership becomes less attractive. Therefore, subway expansion affects the mode usage not only directly by diverting commuters, but also indirectly by decreasing the demand for auto ownership. The coefficient of the treatment indicator catches both of the effects when not controlling for auto ownership, while it catches only the direct effect if controlling for auto ownership. In column (3) and (4), I run the regression with and without auto ownership, respectively.

As shown in Table 3, I find evidence of a positive and statistically significant effect of the subway expansion on subway usage and a negative and statistically significant effect on auto usage in all four specifications. The effect on bus usage is not statistically significant. The effect on walking and bicycling is statistically significant when controlling for demographic variables. Column (4) is the full specification, so I use column (4) as the main results. Panel A indicates that a decrease in the distance to the station increased the percent distance traveled by subway by 0.0254 (from 0.025 to 0.05), which is a 98.3 % change. Panel B shows that percent distance traveled by auto decreased by 0.06 (from 0.303 to 0.243), which is a 19.8% change. Panel C shows that the effect on percent distance traveled by bus is -0.013, which is a 5% decrease (from 0.262 to 0.249) and not statistically significant. Panel D shows that percent distance traveled by walking and bicycling increased by 0.048, which is an 11.8% increase (from 0.409 to 0.457). The results indicate that the subway expansion diverted commuters from auto toward subway, while having no significant effect on bus passengers. The increase in the walking and bicycling distance indicates that walking and bicycling are complements to subway travel, rather than substitutes.

A comparison of columns (3) and (4) shows that the effects remain stable to the control for auto ownership. This indicates that the indirect effect of the subway expansion on mode usage through changing the demand for auto ownership is small. This finding is confirmed by comparing the auto ownership trajectories between the treatment group and the control group. The graphic analysis and the regression results are available in Appendix A.

In Table 4, I show that the effect estimates are robust to econometric models and alternative definitions of mode usage. Column (1) lists the main results from column (4) of Table 1 for comparison. Column (2) of Table 4 uses a tobit model to take account of censoring of the dependent variable at zero and one. The marginal effects are reported. In column (3) and (4), the mode usage is defined as a binary variable, which equals 1 if subway, bus, auto, or walking and bicycling, respectively, is the main mode of the trip, 0 otherwise. The main mode is defined as the mode covering the largest distance of a trip. In column (5) and (6), the mode usage is also defined as a binary variable, which equals 1 if subway, bus, auto, or walking and bicycling, respectively, is involved in a trip, 0 otherwise. Column (3) and (5) are linear probability models. Column (4) and (6) are logistic models. Marginal effects are reported. The estimates remain stable across these specifications.

Evaluating the Underlying Assumptions

In order to interpret these estimates as an unbiased measure of the subway expansion impacts, some important assumptions must hold - in particular, conditional unconfoundedness and stable unit treatment values. Although these assumptions are not directly testable in principle, the following are steps we can take to assess their plausibility.

Assessing Unconfoundedness

First, the above analysis assumes that the mode usage of the two groups have similar trajectories over time absent any treatment effect, conditional on observable individual characteristics (e.g. age, income, gender, occupation, auto ownership). I have shown that this assumption holds by graphing and comparing the pre-treatment mode usage of the late treatment group and those of the control group. Here, I use formal econometric models to verify the graphical results in two ways. First, if the pre-treatment usage trajectories indeed are similar, the double difference $\left(\bar{Y}^m_{g_{2,2008}} - \bar{Y}^m_{g_{2,2007}}\right) - \left(\bar{Y}^m_{g_{1,2008}} - \bar{Y}^m_{g_{1,2007}}\right)$ should estimate zero, where g_1 is the control group, and g_2 is the late treatment group. Second, if the effects of the treatments in 2008 and 2009 are similar, restricting the sample to the control group and the late treatment group should not change the results of the full sample.

To test whether the pre-treatment mode usage trajectories are similar between the later treatment group and the control group, I restrict the sample to the two groups in 2007 and 2008. I define a fake treatment indicator, which equals 1 for the late treatment group in 2008, 0 otherwise. I regress the mode usage on the fake treatment indicator, year dummies, TAZ dummies, district by year dummies, and demographic variables. The coefficient of the fake treatment indicator is expected to estimate zero. Results are shown in column (1) of Table 5. The estimates for all of the four modes are indeed small and not statistically significant.

To estimate the effect of the subway expansion on the late treatment group, I exclude the early treatment group. As shown in column (2) of Table 5, the estimates are similar to the main results. One concern is that the effect on subway usage is smaller and not significant. Smaller sample size could be the reason for this imprecise estimation. Appendix B does a further test and shows that the difference in the effect on subway usage between the two treatment groups is not statistically significant.

Assessing the Stability of Unit Treatment Values

The estimation strategy also requires that the potential mode usage of one individual is independent of the treatment status of other individuals. If the mode usage in the control group was changed by the expansion, the counterfactual estimates would be biased, and the estimates of expansion impacts would, therefore, also be biased.

There are two potential ways in which this assumption might be violated. The first is through traffic congestion alleviation. Commuters are diverted from autos by the new subway lines and therefore the whole road network in Beijing benefits from fewer autos on the road. If the control group reacts to the reduced congestion by driving more, the counterfactual auto usage would be biased. The reaction is not empirically tractable, and neither is the violation of the stable unit treatment values assumption, unless we generate some specific hypothesis regarding how the violation would manifest itself. The hypothesis is that, if traffic congestion is alleviated disproportionately in areas with major destinations, we would expect to find larger treatment effects when the control group is restricted to those areas. I therefore restrict the control group to the four inner districts, which are within the 3rd ring road. That is the most developed area in Beijing, and also the most congested area, with the central business district in it. When there is less driving to work, this area is expected to experience more congestion alleviation than other, less congested areas. The results in column (3) of Table 5 show that restricting the control group to be the four inner districts does not significantly affect the estimated effects.

Another potential violation of the assumption is through self-selective migration. If untreated commuters who prefer the subway are attracted to the treated TAZs, this would decrease the average subway usage of the control group, and exaggerate the estimates of the subway expansion impacts. Again, I generate a specific hypothesis of how this violation would manifest itself. Because the old subway lines have been there for years, commuters with subway preference have settled in nearby TAZs (which could be in the control group or treatment group), so the new lines are not likely to induce large migration of these commuters. It is possible that some commuters prefer the subway, but live farther away due to reasons such as the high housing price and limited housing supply in the nearby areas. The new lines put more areas within walking distance, and therefore may induce the migration of these commuters. If this kind of migration exists, we would expect to find smaller treatment effects when the control group is restricted to nearby TAZs. Column (4) of Table 5 reports SATT estimates obtained using only data from TAZs within 1 kilometer distance of a subway station as controls. Estimated expansion effects are not significantly impacted. This is as expected, as mentioned in the data section.

Without a large housing supply or formal rental markets in highly populated urban Beijing, large scale migration is not likely to happen within a one year time span in this area.

Treatment Effect Heterogeneity

In this subsection, I investigate three types of treatment effect heterogeneity. First, I look into three treatment levels. The distance changes are not the same across TAZs; therefore, the effects are not homogeneous. Next, I ask whether the changes in mode usage are correlated with demographics. Finally, I study the effects of the distance reduction at destination.

Heterogeneous Treatment Levels

The improvement in rail transit accessibility is heterogeneous across treated TAZs. Some TAZs ended up within walking distance of a subway station after not being so (out-in treatment). Some other TAZs were within walking distance before the treatment and ended up even closer (in-in treatment). The rest of the TAZs ended up closer but still beyond walking distance (out-out treatment). We expect to see different mode usage changes across these three groups of treated TAZs. To allow for such differences, I estimate the following regression:

$$Y_{izdt}^{m} = \alpha + \boldsymbol{\beta}'\boldsymbol{X_{it}} + \tau D_{zt} + \theta_1 D_{zt}\mathrm{h}_{\mathrm{zt}}^{\mathrm{in}} + \theta_2 D_{zt}\mathrm{h}_{\mathrm{zt}}^{\mathrm{out}} + c_z + \eta_t + \varphi_{dt} + \nu_{izt} \quad (3)$$

where $\mathrm{h}_{\mathrm{zt}}^{\mathrm{in}}$ is a binary variable which equals 1 if TAZ z is within walking distance before the expansion, 0 otherwise; $\mathrm{h}_{\mathrm{zt}}^{\mathrm{out}}$ equals 1 if TAZ z remains beyond walking distance after the expansion, 0 otherwise. Estimation of parameter θ_1 and parameter θ_2 facilitates a test of whether the treatment effect is heterogeneous with respect to different treatment levels. I experiment with 1 kilometer and 2 kilometers as walking distance.

Table 6 summarizes the results of estimating equation (3). The coefficient of $treatment$, τ, is the estimate of out-in treatment effect. The coefficient of $treatment \times\ I\ (in - in)$, θ_1, is the estimate of the difference between the out-in treatment effect and the in-in treatment effect; while the coefficient of $treatment\ \times\ I\ (out - out)$, θ_2, is the estimate of the difference between the out-in treatment effect and the out-out treatment effect. Most of the estimates of θ are not statistically significant, except those in column (2). This shows that getting into a 1 kilometer radius circle of a subway station after being located farther away increased average percent distance traveled by subway by 0.0404. Starting from within the 1 kilometer radius circle and ending up even closer increased average percent distance traveled by subway by 0.098. Getting closer to a subway but remaining beyond walking distance had little effect on subway usage.

Given that the groups affected by these three treatment levels had very different subway usage before the treatment, I calculate the effects as percentage changes, defined as the change in mode usage divided by the mode usage before being treated. Results are listed in Table 7. Walking distance is defined as 2 kilometers in panel A. More than half of the treated TAZs ended up within walking distance after being beyond walking distance, 32% of them were already within walking distance before the treatment, and 14% remained beyond walking distance after the treatment. The subway usage in out-in treated TAZs almost tripled, which is much larger than the subway usage increase in other treated TAZs. The auto usage decreases in the out-in and in-in treated TAZs were larger than the decrease in the out-out treated TAZs. This indicates that the commuters who ended up within walking distance after previously living farther from the subway station are more likely to switch toward subway use than the commuters who remained beyond walking distance. I also experiment with defining walking distance as 1 kilometer. The results are similar, as shown in panel B of Table 7.

Heterogeneous Treatment Effects across Demographics

I am also interested in investigating whether treatment effects vary systematically across individuals with different socioeconomic characteristics. In particular, I ask whether auto owners and commuters with higher income reacted similarly to the commuters without autos and those with lower incomes. I estimate the following regression:

$$Y_{izdt}^{m} = \alpha + \boldsymbol{\beta}'\boldsymbol{X_{it}} + \boldsymbol{\delta}'\boldsymbol{X_{it}}D_{zt} + \tau D_{zt} + c_z + \eta_t + \varphi_{dt} + \nu_{izt} \quad (4)$$

The parameter vector $\boldsymbol{\delta}$ facilitates a test of whether the treatment effect is heterogeneous with respect to demographics included in X. To investigate the effect heterogeneity across auto ownership, I include auto ownership, driver's license, and their interaction term in X. I cannot directly identify individuals as auto owners because auto ownership is recorded as household information. So I define an auto owner as an individual who has a driver's license and is a member of a household that has one or more autos. By including auto ownership, driver's license, and the interaction term, I distinguish four types of auto users: (1) those having an auto and a driver's license (usually the auto owners, who drive their own autos); (2) those having an auto but no driver's license (usually the owner's spouse or children, who ride in the auto); (3) those having a driver's license but no auto (who drive borrowed autos or company autos); and (4) those having neither an auto nor a driver's license (who ride company autos or take taxis).

The results are listed in Table 8. The coefficient of $treatment \times auto\ ownership \times driver's\ license$ is statistically significant in column (3) and (4), the estimations of the effect on auto usage. This indicates that auto usage of auto owners decreased more than that of commuters without an auto or a driver's license. This is because auto owners have much greater auto usage to begin with. As shown in panel A of Table 9, the average percent distance traveled by auto is 0.69 for auto owners, while it is 0.025 for commuters without an auto or a driver's license. I measure the impacts as percent changes and report the results in panel A of Table 9. For commuters without an auto or a driver's license, subway usage increased by 105.2%, and auto usage decreased by 262.8%. For auto owners, subway usage increased by 21.7%, and auto usage decreased by 13.8%. Compared to the commuters without an auto or a driver's license, auto owners are much less likely to be diverted from autos toward the subway.

To investigate the effect of heterogeneity across income levels, I also include household income in X. As shown in Table 8, the coefficient of $treatment \times income$ is not statistically significant in any of the regressions. Again, the commuters with different income have different mode usage to begin with. As shown in panel B of Table 9, the percent distance traveled by auto is 0.19 for commuters with income level 2, while it is 0.41 for commuters with income level 5. I measure the impacts as percent changes and report the results in panel B of Table 9. This shows that commuters with higher income were less likely to switch from autos, compared to commuters with lower income.

Treatment at Destination

In all the analyses above, I focus on the treatment at origin, as I define the treatment as whether there is a change in the distance between home TAZ and the nearest subway station. Rail accessibility is also improved when the distance between the place of work and a subway station is decreased. In this section, I estimate the effect of the treatment at destination by the following regression:

$$Y_{izdt}^{m} = \alpha + \boldsymbol{\beta}'\boldsymbol{X_{it}} + \tau D_{zt} + \tau^{d} D_{zt}^{d} + c_z + \eta_t + \varphi_{dt} + \nu_{izt} \quad (5)$$

where D_{zt}^{d} is the indicator of treatment at destination, which equals 1 if the distance between the work TAZs and the nearest subway station is decreased at time t, 0 otherwise.

Results are listed in Table 10. The treatment at destination does not have statistically significant effects on the usage of subway, autos, or buses. The effect on walking and bicycling is significant at the 10% significance level. The estimated impacts of the treatment at origin are not changed significantly by the additional treatment indicator. Compared to the treatment at origin, the impact of the treatment at destination on mode usage is minor. The possible reason is that the main business areas are covered by the old subway lines. The main function of the new lines (Line 5, 8, and 10) is to collect and bring commuters to those major destinations. Therefore the effect of treatment at origin is large, while the effect of treatment at destination is small. When the whole of urban Beijing is covered by subway lines, as in the 2015 Plan, we expect to see the effect of the treatment at destination for the additional lines.

Effect on the Number of Trips

In this section, I ask whether the number of trips and the trip distance are increased by the subway expansion. As the expansion makes commuting more convenient and faster, commuters in the treatment group may respond to the convenience by taking more trips or going to farther away places. Table 11 summarizes the results of estimating equation (2) with different dependent variables. In column (1), the dependent variable is the number of work trips taken by a commuter in a week day. The estimate is small and not statistically significant. This indicates that commuters did not increase the frequency of work trips in response to the accessibility improvement. Column (2) to column (5) measure the effect of the expansion on trip distances. In column (2) and column (4), the trip distance is measured as the sum of reported distances of trip segments and the point to point distance calculated by ArcGIS, respectively. Column (3) and (5) take the natural logarithm of the reported distances and the GIS measured distances. The estimates are small and not statistically significant in columns (2) through (5). This indicates that commuters did not travel to a farther place to work when the rail transit accessibility was improved.

In addition, as the subway system diverts commuters away from automobiles, ground travel congestion is reduced. Commuters in both the treatment group and the control group benefit from the congestion alleviation, and both of them may respond by traveling more. Therefore, I investigate the trajectories of the number of trips and the trip distance. I compare the mean differences between 2007 and 2009. The t-statistic is -0.35 for the number of trips, -0.53 for the reported trip distance, and 0.67 for the measured trip distance. There is no statistically significant evidence that commuters respond to the congestion alleviation by traveling farther or more often to work.

Conclusion

The Beijing municipal government is spending over $30 billion on new urban rail transit lines to transform Beijing into a "public transportation city."[16] This investment is intended to reduce the air pollution and congestion caused by the rapid increase in auto usage. As in other mass transit investments, Beijing's goals are best met if the new rail lines divert riders from travel modes that cause congestion and pollution, such as automobiles, rather than generating new riders from those who walked or rode bicycles. In this paper, I utilize the rapid rollout of new subway lines in urban Beijing to test whether the improvement of subway accessibility diverted commuters toward the subway, from which modes the diversion came, and how commuters with different socioeconomic characteristics reacted to the improvement.

The results indicate that the new subway lines increased the percent distance traveled by subway by about 98.3% and decreased the percent distance traveled by autos by 19.8% in the treated areas, on average, relative to the untreated areas. The percent distance traveled by buses decreased by 5% and is not statistically significant. Along with the increase in subway usage, walking and bicycling distance increased by 11.8%, indicating that they are complements to subway use, rather than substitutes. The results are robust to specifications and alternative definitions of mode usage. I also find evidence that auto owners and commuters with higher income were less likely to switch from auto use toward subway use.

What does the 19.8% decrease in auto usage mean to air quality in economic terms? The average work trip distance in the sample is 8 kilometers, and therefore 1.6 kilometers is diverted from auto per trip. When the 2015 Plan is completed, all the residents in urban Beijing will be within walking distance of at least one subway station. Supposing that two-thirds of them make one round trip per day for work (based on the sample statistics), the total distance saved in auto usage will be 17 million kilometers per day. According to Parry and Small (2009), the cost of local and global air polluting, congestion, and accidents varies from $ .46 per mile for Washington DC to $ 2.42 per mile for London. Using the same cost range, the cost saved by diverting commuters from autos will be $5 million to $26 million per day. Supposing that there are 250 week days per year, $1 to 6 billion will be saved in the first year of completion of the 2015 Plan. Regardless of the precise numbers used to interpret the magnitude of the air quality

[16] Source: "Rail Transit Plan of Beijing by 2015" (forthcoming), Beijing Municipal Commission of Urban Planning.

and congestion alleviation benefits,[17] the calculation indicates that the effects of rail transit infrastructure are economically substantial.

[17] Although the value of time and value of statistical life are possibly lower in urban Beijing than Washington DC because of the lower average wage, the cost of air pollution is not necessarily lower, given the higher population in density urban Beijing. The population density is 5500 people / square km in urban Beijing, while it is 3400 people / square km in Washington DC, and 5200 people/square km in London.

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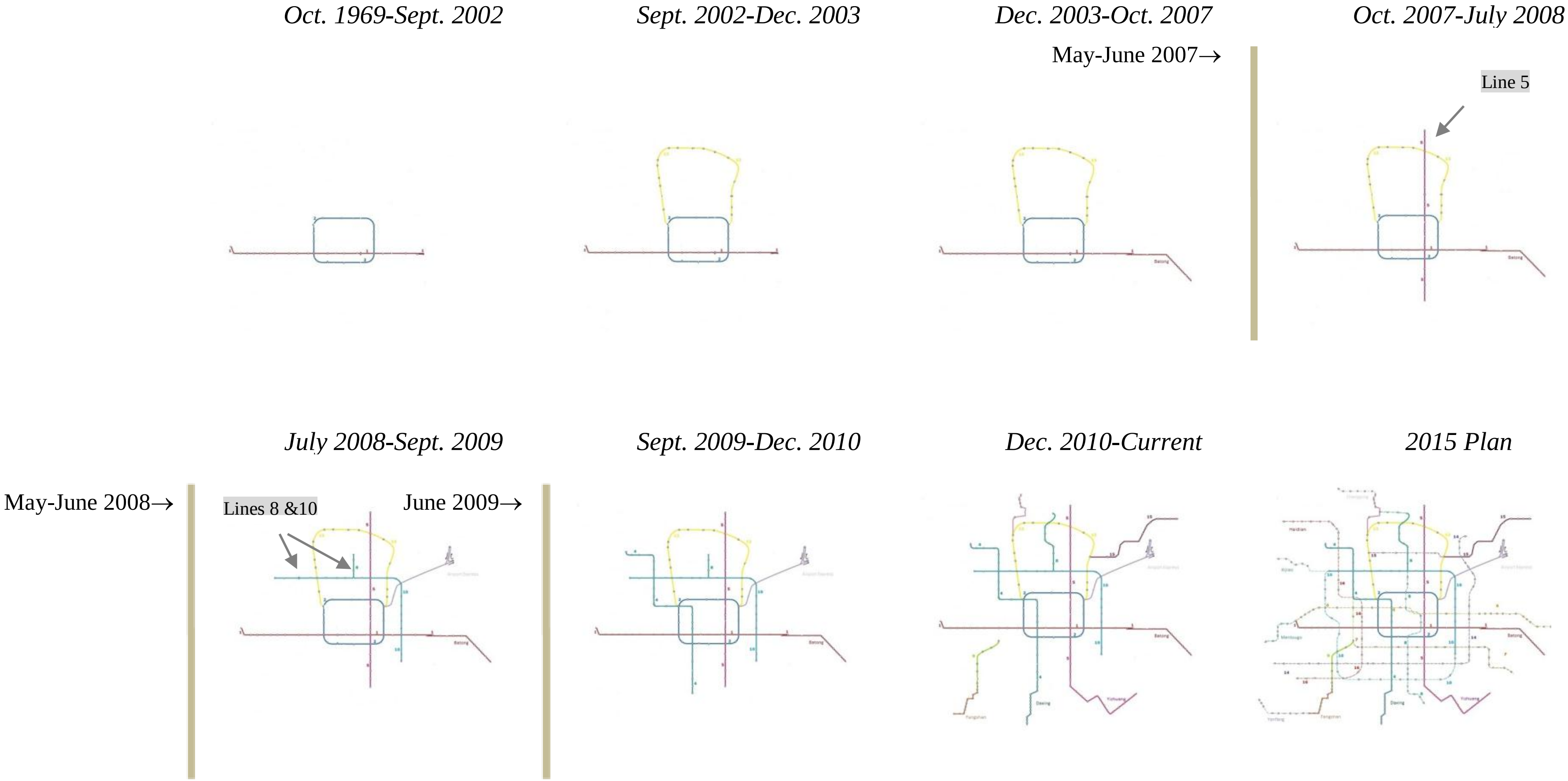
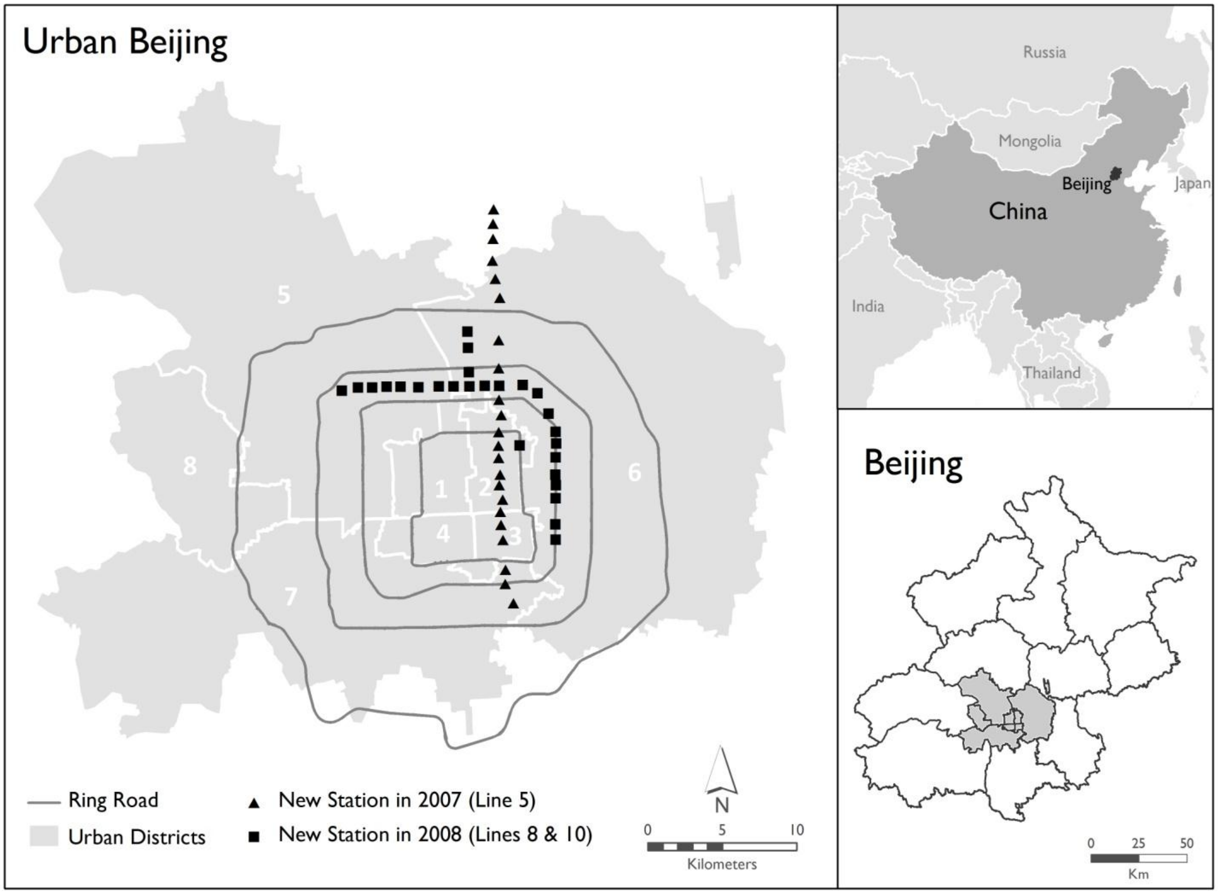
Figures and Tables

Figure 1. Beijing Subway System Expansion History and 2015 Plan



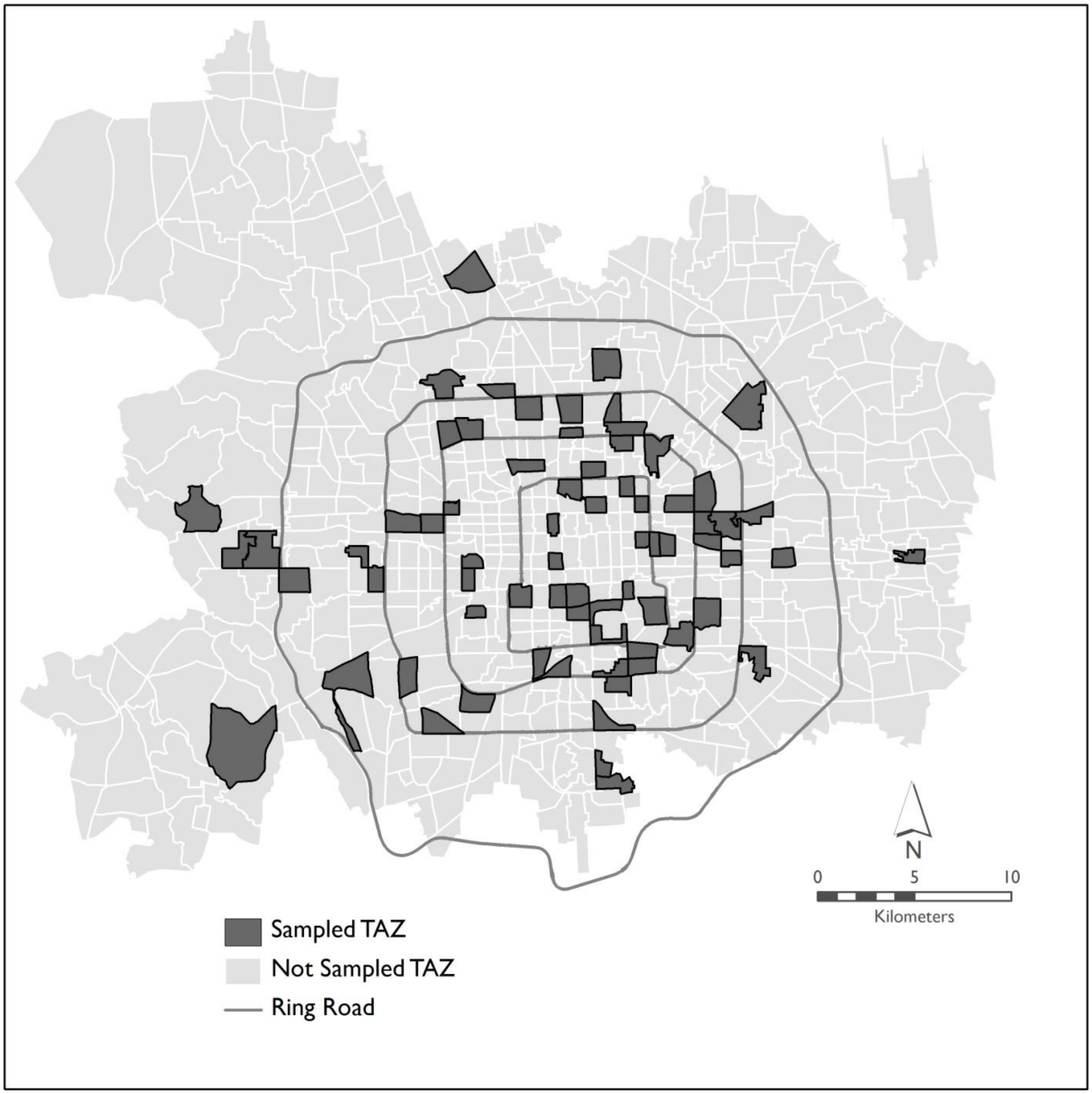
Notes: The vertical lines show survey dates relative to the subway expansion. Between the three rounds of surveys, Line 5, Line 8 and Line 10 started operation.

Figure 2. Map of Beijing and Subway Line 5, 8, and 10



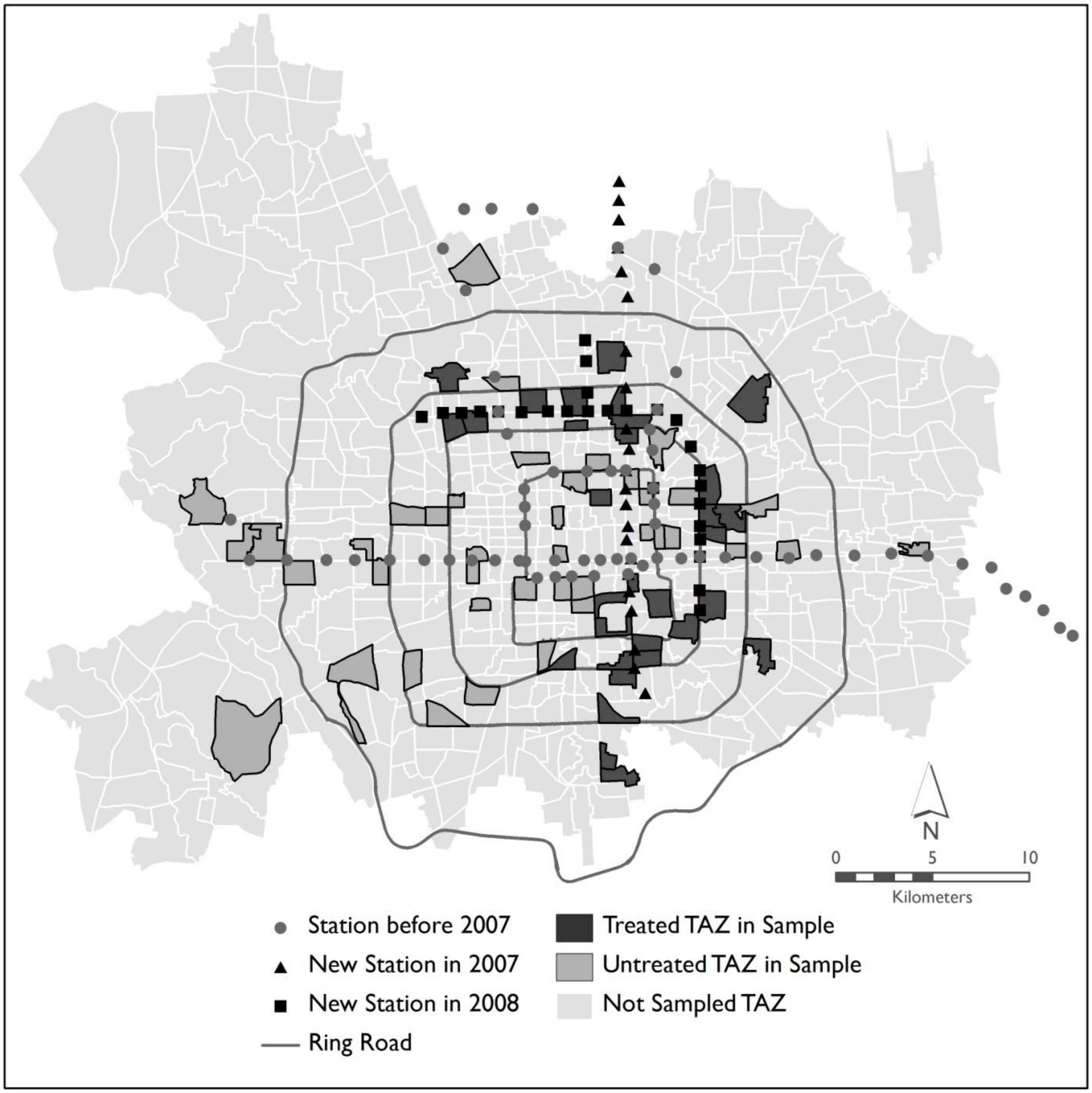
Notes: The area studied in this paper is urban Beijing, including the eight administrative districts at the center of Beijing. Line 5, Line 8, and Line 10 cut the ring roads vertically and horizontally. The areas covered by the new lines are geographically and economically representative.

Figure 3. Traffic Analysis Zones Surveyed in All Three Years



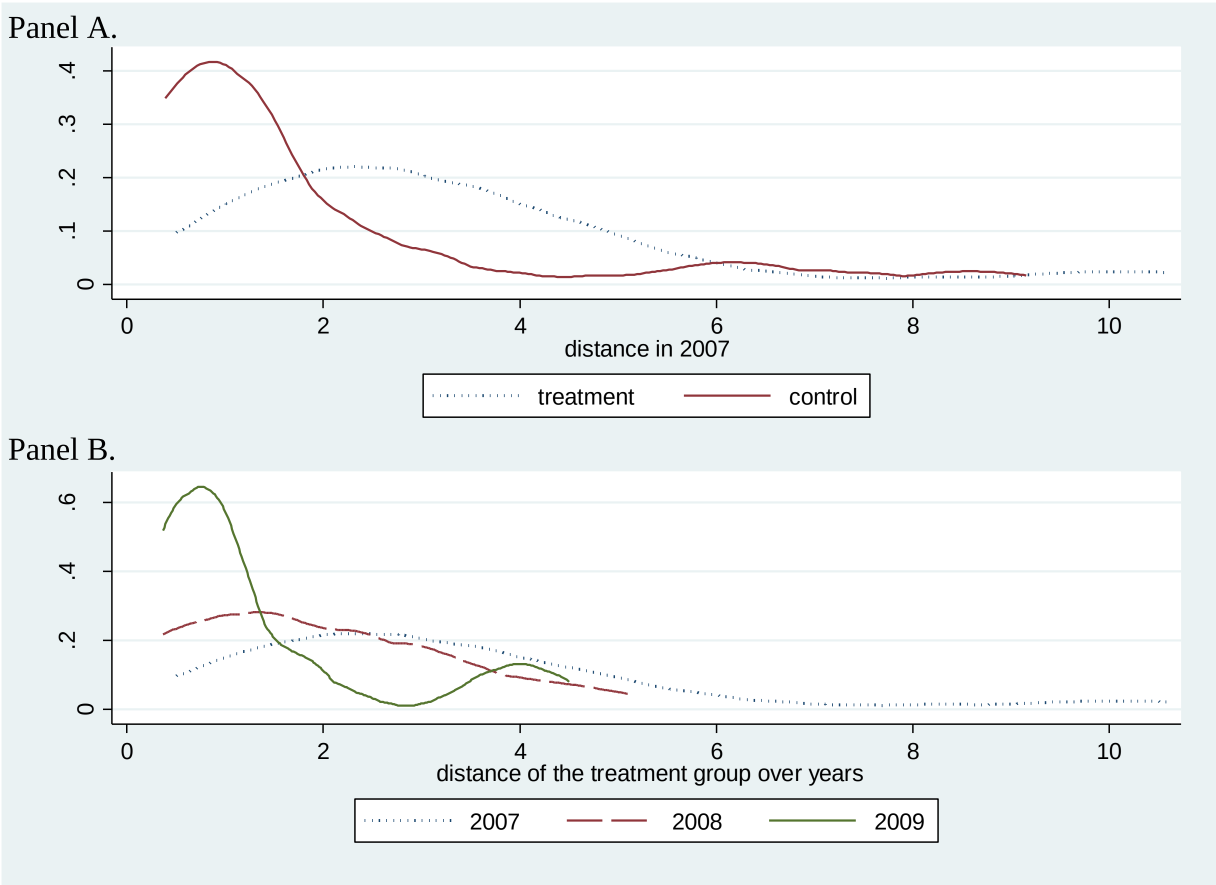
Notes: 71 TAZs are surveyed in all three years from 2007-2009. They are scattered mostly within the 5th ring road and are geographically representative. I restrict the sample to households from these 71 TAZs.

Figure 4. Treated TAZs



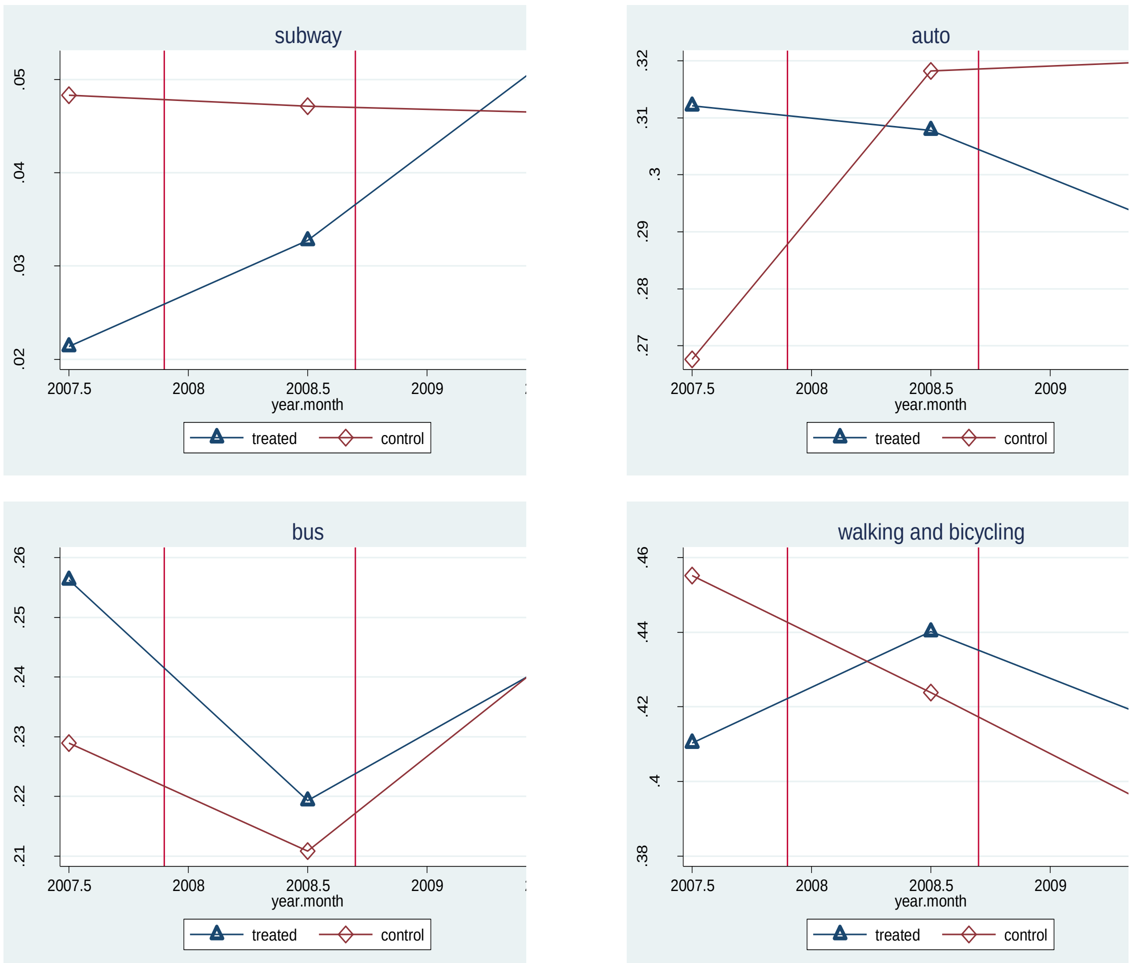
Notes: A TAZ is defined to be treated if its distance to the nearest subway station is decreased in 2008 or 2009. In the sample, 31 TAZs are treated and 40 TAZs are not treated.

Figure 5. Distribution of Distances to the Nearest Subway Station



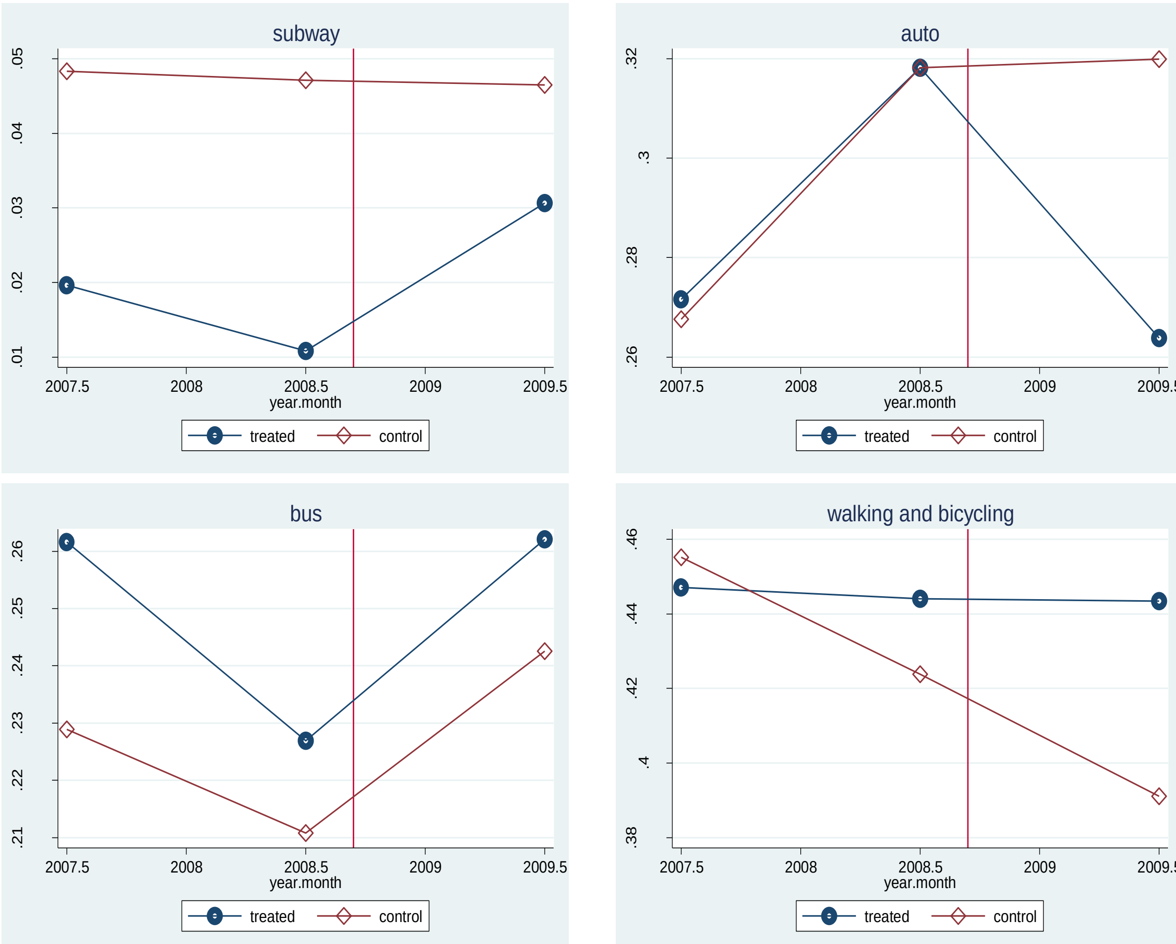
Notes: In 2007 (pre-treatment period), the treatment group and the control group had the same range of distances to the nearest subway station. The average distance of the treatment group fell by 1.39 kilometers (3.35 kilometers to 1.96 kilometers) from 2007 to 2008, and fell by 0.57 kilometers (1.96 kilometers to 1.39 kilometers) from 2008 to 2009.

Figure 6. Mode Usage Trajectories: Treatment Group vs. Control Group



Notes: The graphs compare the average percent distance traveled by subway, autos, buses, and walking and bicycling between the treatment group (31 TAZs) and the control group (40 TAZs). The two vertical lines are the treatments (the opening of line 5 in October 2007 and the opening of line 8 and line 10 in July 2008). 19 TAZs in the treatment group are treated by the first treatment and are referred as the early treatment group. The other 12 TAZs are treated by the second treatment and are referred as the later treatment group.

Figure 7. Mode Usage Trajectories: Late Treatment Group vs. Control Group



Notes: The graphs compare the average percent distance traveled by subway, autos, buses, and walking and bicycling between the late treatment group (12 TAZs) and the control group (40 TAZs). The vertical line is the second treatment (the opening of line 8 and line 10 in July 2008). The pre-treatment trajectories between the two groups are similar. Although the pre-treatment trajectories seem different for walking and bicycling, the mean test suggests that the difference is not statistically significant.

Table 1. Sample by District

District	TAZ in total	2009		2008		2007	
		TAZ	Household	TAZ	Household	TAZ	Household
1	45	9	201	12	219	15	256
2	31	8	160	11	215	18	354
3	15	6	120	8	163	11	250
4	21	9	180	11	202	11	276
5	188	36	820	35	859	52	941
6	209	43	918	49	1044	54	1066
7	106	25	522	26	564	39	611
8	22	7	140	8	158	11	294
Total	637	143	3061	160	3424	211	4048

Notes: Repeated cross-sectional data. In each of the eight districts in urban Beijing, households were randomly selected each year, stratified by Traffic Analysis Zone (TAZ). On average, one third of the TAZs were selected in each district, and about 25 households were drawn for interviews in each TAZ.

Table 2. Summary Statistics

Group	Variable	31 TAZs in the treatment group per year 40 TAZs in the control group per year					
		2007		2008		2009	
		Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
Treatment	Subway usage (%)	2.1358	3.4283	3.2739	4.5024	5.1992	5.8859
	Auto usage (%)	31.2101	12.6126	30.7803	6.4860	29.1015	11.6021
	Bus usage (%)	25.6257	9.6032	21.9278	10.2254	24.1866	10.0207
	Walking and bicycling (%)	41.0285	14.2781	44.0181	14.0180	41.5127	15.6235
	Reported trip distance (km)	7.8959	2.9338	8.8949	3.1983	7.3064	3.0268
	Measured trip distance (km)	5.8891	1.8435	5.7917	2.0223	5.7659	1.9142
	Number of trips	1.0416	0.0912	1.0710	0.0961	1.0533	0.0842
	Income (level 1-8)	3.7680	0.6657	4.0522	0.4094	4.2755	0.3466
	Auto ownership (1=with, 0=without)	0.5154	0.1926	0.5312	0.1276	0.5705	0.1641
	Gender (1=male, 0=female)	0.5505	0.1235	0.5729	0.0735	0.5560	0.1189
	Age (year)	35.5192	5.0044	35.2776	2.5510	35.9215	2.2655
	Driver's license (1=with, 0=without)	0.4879	0.1382	0.4119	0.0964	0.4354	0.1280
Control	Subway usage (%)	4.8316	4.7792	4.7108	4.8717	4.6468	4.5133
	Auto usage (%)	26.7638	10.1385	31.8218	7.8543	31.9924	10.2083
	Bus usage (%)	22.8915	10.7761	21.0815	10.6447	24.2577	10.1783
	Walking and bicycling (%)	45.5132	13.8425	42.3858	13.7418	39.1031	14.0169
	Reported trip distance (km)	7.8020	2.7267	9.6689	3.6515	7.8220	2.5631
	Measured trip distance (km)	5.9741	1.7652	6.0913	2.2462	6.4622	2.2282
	Number of trips	1.0588	0.0746	1.0599	0.0693	1.0415	0.0673
	Income (level 1-8)	3.5732	0.6680	4.2150	0.4592	4.3601	0.4579
	Auto ownership (1=with, 0=without)	0.4696	0.1567	0.5430	0.1559	0.5716	0.1285
	Gender (1=male, 0=female)	0.5179	0.0945	0.5690	0.0944	0.5741	0.0757
	Age (year)	36.0826	2.6967	34.9776	4.4709	35.8318	2.4817
	Driver's license (1=with, 0=without)	0.4121	0.1119	0.4462	0.1403	0.4491	0.1072

Notes: I report the summary statistics of the work trips from the balanced sample of TAZs (71 TAZs that are surveyed in all three years).

Table 3. Effect of Subway Expansion on Mode Usage

Dep. Variable: percent distance traveled by a mode (= distance traveled by a mode/trip distance)				
	(1)	(2)	(3)	(4)
Panel A. subway				
	0.0241***	0.0176**	0.0248***	0.0250***
	(0.00892)	(0.00834)	(0.00909)	(0.00905)
Panel B. auto				
	-0.0446**	-0.0504**	-0.0651**	-0.0601***
	(0.0204)	(0.0234)	(0.0250)	(0.0221)
Panel C. bus				
	-0.0249	-0.0201	-0.0116	-0.0132
	(0.0230)	(0.0228)	(0.0244)	(0.0229)
Panel D. walking and bicycling				
	0.0454	0.0528	0.0519**	0.0483**
	(0.0345)	(0.0339)	(0.0224)	(0.0224)
group indicator	x			
year dummies	x			
TAZ dummies		x	x	x
survey date dummies		x	x	x
district by year dummies		x	x	x
income, gender, age, occupation			x	x
auto ownership, driver's license				x
number of observations	7,585	7,585	7,547	7,547

Notes: Observations are at individual trip level. Only work trips are studied in this paper. Mode usage is measured as the percent distance traveled by a mode. Subway expansion is the treatment, which equals 1 if the distance to the nearest subway station is decreased in 2008 or 2009, 0 otherwise. Standard errors are clustered at the TAZ level. *,**, *** indicate 10%, 5%, and 1% significance level, respectively.

Table 4. Robustness to Alternative Definitions of Mode Usage and Models

Dep. Variable:	Percent Distance		Main Mode		Ever Take	
	(1)	(2)	(3)	(4)	(5)	(6)
	Linear	Tobit	LPM	Logit	LPM	Logit
Panel A. subway						
	0.0250***	0.0322***	0.0281**	0.0380***	0.0300***	0.0407***
	(0.00905)	(0.0019)	(0.0110)	(0.0117)	(0.0108)	(0.0113)
Panel B. auto						
	-0.0601***	-0.0564***	-0.0629***	-0.0573**	-0.0672***	-0.0682**
	(0.0221)	(0.0219)	(0.0224)	(0.0238)	(0.0236)	(0.0267)
Panel C. bus						
	-0.0132	0.0000771	-0.0106	-0.0093	0.00616	0.0098
	(0.0229)	(0.0211)	(0.0251)	(0.0231)	(0.0268)	(0.0278)
Panel D. walking and bicycling						
	0.0483**	0.0349**	0.0470*	0.0827**	0.0112	0.0191**
	(0.0224)	(0.0156)	(0.0244)	(0.0352)	(0.0121)	(0.0085)
TAZ dummies	x	x	x	x	x	x
survey data dummies	x	x	x	x	x	x
district by year dummies	x	x	x	x	x	x
demographic variables	x	x	x	x	x	x
number of observations	7,547	7,547	7,547	7,547	7,547	7,547

Notes: In column (1) and (2), the dependent variable is defined as percent distance traveled using that mode, which is a continuous variable between 0 and 1. In column (3) and (4), the dependent variable is defined as a binary variable, which equals 1 if the mode is the main mode (covering the longest distance) of the trip, 0 otherwise. In column (5) and (6), the dependent variable equals 1 if the mode is involved in the trip, 0 otherwise. Marginal effects are reported in the tobit model and the logit models. Standard errors are clustered at the TAZ level. *,**, *** indicate 10%, 5%, and 1% significance level, respectively.

Table 5. Indirect Test of Unconfoundedness

Dep. Variable: percent distance traveled by a mode (= distance traveled by a mode/trip distance)				
	(1)	(2)	(3)	(4)
Panel A. subway				
	-0.000959	0.0185	0.0339**	0.0241**
	(0.0147)	(0.0142)	(0.0161)	(0.0110)
Panel B. auto				
	0.0312	-0.0884***	-0.0428	-0.0459**
	(0.0262)	(0.0298)	(0.0281)	(0.0224)
Panel C. bus				
	-0.0220	0.0302	-0.0271	-0.0216
	(0.0296)	(0.0296)	(0.0272)	(0.0271)
Panel D. walking and bicycling				
	-0.00820	0.0398	0.0360	0.0434*
	(0.0317)	(0.0317)	(0.0258)	(0.0245)
TAZ dummies	x	x	x	x
survey data dummies	x	x	x	x
district by year dummies	x	x	x	x
demographic variables	x	x	x	x
number of observations	5,541	5,541	4667	5,494

Notes: Column (1) tests whether the pre-treatment mode usage trajectories are similar between the late treatment group and the control group. Column (2) estimates the average treatment effects on the late treatment group. Column (3) and (4) test for the plausibility of the SUTVA assumption. In column (3), the control group is restricted to the TAZs that are within a 1 km radius circle of a subway station. In column (4), the control group is restricted to the TAZs in the four inner districts. Standard errors are clustered at the TAZ level. *,**, *** indicate 10%, 5%, and 1% significance level, respectively.

Table 6. Treatment Effect Heterogeneity: Three Treatment Levels

Dep. Variable: percent distance traveled by a mode (= distance traveled by a mode/trip distance)								
	subway		auto		bus		walking and bicycling	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatment	0.0312**	0.0404***	-0.0718**	-0.0798***	-0.0311	-0.0143	0.0717**	0.0537**
	(0.0129)	(0.0116)	(0.0290)	(0.0209)	(0.0229)	(0.0259)	(0.0277)	(0.0237)
treatment x I (in2-in2)	-0.00739		-0.00935		0.0597		-0.0429	
	(0.0185)		(0.0363)		(0.0392)		(0.0320)	
treatment x I (out2-out2)	-0.0273		0.100**		-0.00441		-0.0687	
	(0.0167)		(0.0431)		(0.0361)		(0.0414)	
treatment x I (in1-in1)		0.0576***		0.0259		-0.0582		-0.0252
		(0.0213)		(0.0512)		(0.0400)		(0.0508)
treatment x I (out1-out1)		-0.0426***		0.0546		0.00296		-0.0149
		(0.0120)		(0.0412)		(0.0385)		(0.0360)
TAZ dummies	x	x	X	x	x	x	x	x
survey data dummies	x	x	x	x	x	x	x	x
district by year dummies	x	x	x	x	x	x	x	x
demographic variables	x	x	x	x	x	x	x	x
number of observations	7,547	7,547	7,547	7,547	7,547	7,547	7,547	7,547

Notes: Distance changes are classified into three levels: ending up within walking distance after being beyond walking distance (out-in treatment), ending up closer but still remaining beyond walking distance (out-out treatment), and being within walking distance before the treatment and getting closer afterward (in-in treatment). Walking distance is defined as 2 kilometers and 1 kilometer, respectively. For example, *I (in2-in2)* is a binary variable which equals 1 if the TAZ was within a 2 km radius circle of a subway station before the treatment and ended up closer to another station after the treatment, 0 otherwise. The coefficient of *treatment x I (in2-in2)* catches the treatment effect of heterogeneity between the out2-in2 treatment and the in2-in2 treatment. Standard errors are clustered at TAZ level. *,**, *** indicate 10%, 5%, and 1% significance level, respectively.

Table 7. Measuring Treatment Effect Heterogeneity in Percent Change

Panel A. Walking distance is defined as 2 km

	sample		estimates	effect	percent distance	% change	
subway							
out - in	495	54.0%	0.0312	0.0312	0.0167	187.0%	**
in - in	292	31.9%	-0.0073	0.0239	0.0465	51.4%	*
out - out	129	14.1%	-0.0273	0.0039	0.0113	34.5%	
auto							
out - in	495	54.0%	-0.0718	-0.0718	0.3128	-23.0%	**
in - in	292	31.9%	-0.0094	-0.0812	0.2815	-28.8%	***
out - out	129	14.1%	0.1000	0.0282	0.3145	9.0%	
bus							
out - in	495	54.0%	-0.0311	-0.0311	0.2950	-10.5%	
in - in	292	31.9%	0.0597	0.0286	0.2000	14.3%	
out - out	129	14.1%	-0.0044	-0.0355	0.2773	-12.8%	
walking and bicycling							
out - in	495	54.0%	0.0717	0.0717	0.3755	19.1%	**
in - in	292	31.9%	-0.0429	0.0288	0.4720	6.1%	
out - out	129	14.1%	-0.0687	0.0030	0.3969	0.8%	

Panel B. Walking distance is defined as 1 km

	sample		estimates	effect	percent distance	% change	
subway							
out - in	486	53.1%	0.0404	0.0404	0.0207	195.6%	***
in - in	66	7.2%	0.0576	0.0980	0.0943	104.0%	***
out - out	364	39.7%	-0.0426	-0.0022	0.0193	-11.4%	
auto							
out - in	486	53.1%	-0.0798	-0.0798	0.3349	-23.8%	***
in - in	66	7.2%	0.0259	-0.0539	0.3100	-17.4%	
out - out	364	39.7%	0.0546	-0.0252	0.2594	-9.7%	
bus							
out - in	486	53.1%	-0.0143	-0.0143	0.2819	-5.1%	
in - in	66	7.2%	-0.0582	-0.0725	0.1543	-47.0%	*
out - out	364	39.7%	0.0030	-0.0113	0.2555	-4.4%	
walking and bicycling							
out - in	486	53.1%	0.0537	0.0537	0.3626	14.8%	**
in - in	66	7.2%	-0.0252	0.0285	0.4414	6.5%	
out - out	364	39.7%	-0.0149	0.0388	0.4658	8.3%	

Notes: Treatment effects are calculated as percent changes, defined as the average change in the percent distance ("effect" column in the table) divided by the pre-treatment percent distance ("percent distance" column in the table). Standard errors are clustered at the TAZ level. *,**, *** indicate 10%, 5%, and 1% significance level, respectively.

Table 8. Treatment Effect Heterogeneity across Socioeconomic Characteristics

Dep. Variable: percent distance traveled by a mode (= distance traveled by a mode/trip distance)

	subway		auto		bus		walking and bicycling	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatment	0.0219**	0.0165	-0.0659***	-0.0450	-0.00870	-0.0129	0.0527*	0.0414
	(0.0104)	(0.0213)	(0.0237)	(0.0457)	(0.0279)	(0.0465)	(0.0268)	(0.0514)
treatment x auto ownership x driver's license	0.0352	0.0354	-0.119**	-0.120**	0.0188	0.0190	0.0650	0.0655
	(0.0252)	(0.0253)	(0.0485)	(0.0486)	(0.0455)	(0.0459)	(0.0499)	(0.0497)
treatment x auto ownership	0.0131	0.0120	0.0566**	0.0607**	-0.0167	-0.0175	-0.0530*	-0.0552
	(0.0131)	(0.0151)	(0.0263)	(0.0262)	(0.0288)	(0.0322)	(0.0307)	(0.0333)
treatment x driver's license	-0.0377	-0.0381*	0.0320	0.0335	-0.00306	-0.00335	0.00878	0.00799
	(0.0196)	(0.0197)	(0.0298)	(0.0306)	(0.0405)	(0.0408)	(0.0348)	(0.0345)
treatment x income		0.00143		-0.00552		0.00110		0.00299
		(0.00579)		(0.0101)		(0.00962)		(0.0118)
TAZ dummies	x	x	x	x	x	x	x	x
survey data dummies	x	x	x	x	x	x	x	x
district by year dummies	x	x	x	x	x	x	x	x
demographic variables	x	x	x	x	x	x	x	x
number of observations	7,547	7,547	7,547	7,547	7,547	7,547	7,547	7,547

Notes: Standard errors are clustered at the TAZ level. *,**, *** indicate 10%, 5%, and 1% significance level, respectively.

Table 9. Measuring Treatment Effect Heterogeneity in Percent Change

Panel A: Auto ownership and Driver's license

		sample		effect	percent distance	% change	
Subway							
	no auto	289	31.6%	0.0219	0.0208	105.2%	**
	auto owner	288	31.4%	0.0326	0.1506	21.7%	**
Auto							
	no auto	289	31.6%	-0.0659	0.0251	-262.8%	***
	auto owner	288	31.4%	-0.0963	0.6971	-13.8%	***
bus							
	no auto	289	31.6%	-0.0087	0.3900	-2.2%	
	auto owner	288	31.4%	-0.0097	0.0941	-10.3%	
walking and bicycling							
	no auto	289	31.6%	0.0527	0.5640	9.3%	*
	auto owner	288	31.4%	0.0735	0.1937	37.9%	**

Notes: Standard errors are clustered at the TAZ level. *,**, *** indicate 10%, 5%, and 1% significance level, respectively. See Table 7 for additional notes.

Table 9. Measuring Treatment Effect Heterogeneity in Percent Change

Panel B: Income Levels

	sample		effect	percent distance	% change	
subway						
income level 2	142	15.5%	0.0194	0.0114	170.1%	
income level 3	203	22.2%	0.0208	0.0180	115.7%	**
income level 4	324	35.4%	0.0222	0.0349	63.6%	**
income level 5	181	19.8%	0.0237	0.0289	81.7%	
auto						
income level 2	142	15.5%	-0.0558	0.1928	-29.0%	*
income level 3	203	22.2%	-0.0613	0.2518	-24.3%	**
income level 4	324	35.4%	-0.0667	0.3061	-21.8%	***
income level 5	181	19.8%	-0.0721	0.4065	-17.7%	***
bus						
income level 2	142	15.5%	-0.0107	0.2244	-4.8%	
income level 3	203	22.2%	-0.0096	0.2861	-3.4%	
income level 4	324	35.4%	-0.0085	0.2849	-3.0%	
income level 5	181	19.8%	-0.0074	0.2266	-3.3%	
walking and bicycling						
income level 2	142	15.5%	0.0474	0.5714	8.3%	
income level 3	203	22.2%	0.0504	0.4440	11.3%	*
income level 4	324	35.4%	0.0534	0.3740	14.3%	*
income level 5	181	19.8%	0.0564	0.3380	16.7%	*

Notes: Standard errors are clustered at the TAZ level. *,**, *** indicate 10%, 5%, and 1% significance level, respectively. See Table 7 for additional notes.

Table 10. Effects of the Treatment at Destination

Dep. Variable: percent distance traveled by a mode (= distance traveled by a mode/trip distance)	subway	auto	bus	walking and bicycling
	(1)	(2)	(3)	(4)
treatment	0.0237**	-0.0525**	-0.00654	0.0354
	(0.00973)	(0.0230)	(0.0240)	(0.0222)
treatment at destination	0.00409	-0.0242	-0.0211	0.0412*
	(0.00911)	(0.0201)	(0.0211)	(0.0241)
TAZ dummies	x	x	x	x
survey data dummies	x	x	x	x
district by year dummies	x	x	x	x
demographic variables	x	x	x	x
number of observations	7,547	7,547	7,547	7,547

Notes: treatment at destination equals 1 if the distance between the place to work and the nearest station decreased in 2008 or 2009, 0 otherwise. Standard errors are clustered at the TAZ level. *,**, *** indicate 10%, 5%, and 1% significance level, respectively.

Table 11. Effects of Subway Expansion on Number of Trips and Trip Distance

Dep. Variable:	number of work trips	reported work trip distance	log (reported distance)	distance measured by GIS	log (distance by GIS)
	(1)	(2)	(3)	(4)	(5)
	-0.00088	-0.238	-0.0824	-0.0632	-0.0110
	(0.0161)	(0.542)	(0.0907)	(0.238)	(0.0517)
TAZ dummies	x	x	x	x	x
survey data dummies	x	x	x	x	x
district by year dummies	x	x	x	x	x
demographic variables	x	x	x	x	x
number of observations	7,152	7,547	7,547	7,547	6,255

Notes: All columns have the same specification but have different dependent variables. Standard errors are clustered at the TAZ level. *,**, *** indicate 10%, 5%, and 1% significance level, respectively.

Appendices

Appendix A. Effect of Subway Expansion on Auto Ownership

To test whether auto demand is decreased by rail accessibility improvement in the treatment group, relative to the control group, the auto ownership trajectories for both groups are depicted in Figure A1. Both groups have an upward trajectory in auto ownership. There is no obvious difference between the two groups. This finding is confirmed by formal regression results, as shown in Table A1. The observations are households, since auto ownership is observed at the household level. Column (1) is the basic specification. Column (2) includes TAZ dummies, instead of the group indicator. Column (3) includes household income and district by year dummies. None of the specifications show a statistically significant effect of the subway expansion on auto ownership.

Figure A1. Auto Ownership Trajectories in the Treatment Group and the Control Group

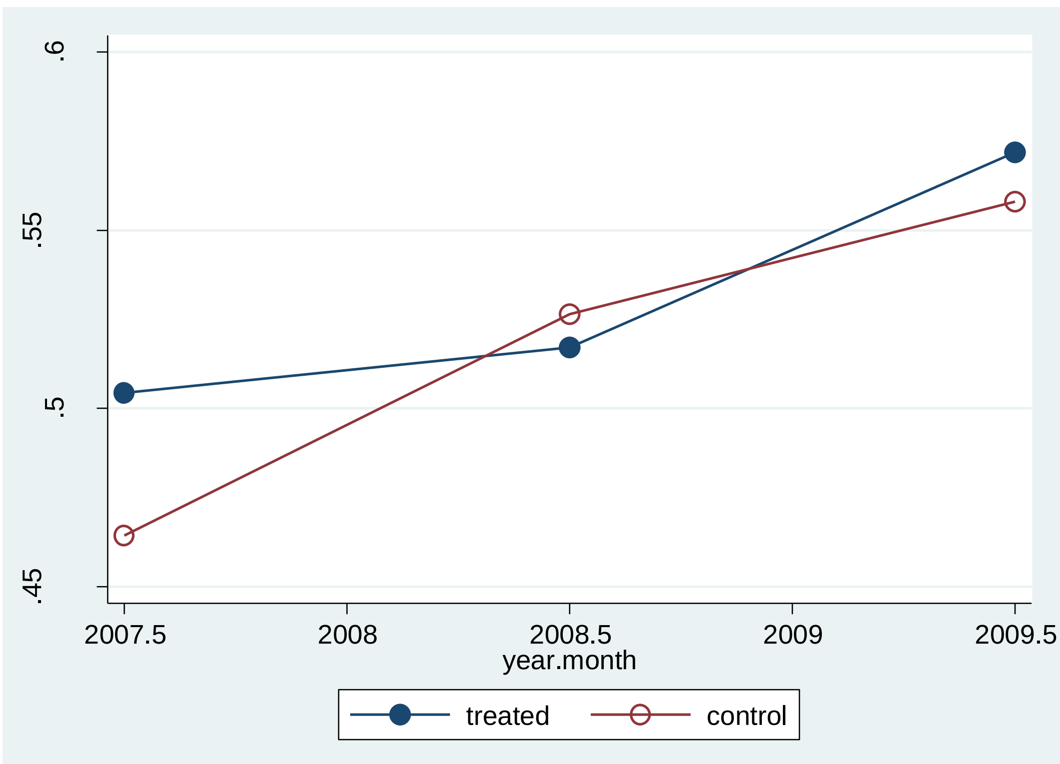


Table A1. Effect of Subway Expansion on Auto Ownership

Dep. Variable: auto ownership, which equals 1 if a household has one or more autos, 0 otherwise.			
	(1)	(2)	(3)
treatment	-0.0226	-0.0233	0.0190
	(0.0256)	(0.0332)	(0.0370)
income			0.168***
			(0.00913)
treatment indicator	x		
year dummies	x	x	x
TAZ dummies		x	x
district by year dummies			x
Observations	4,180	4,180	4,166

Notes: Standard errors are clustered at the TAZ level. *,**, *** indicate 10%, 5%, and 1% significance level, respectively.

Appendix B: Effects of the Early Treatment and the Late Treatment on Mode Usage

I test whether the early treatment and the late treatment have similar effects on mode usage. I define a binary variable *I (late treatment group),* and interact it with *treatment.* If the two treatment groups have similar effects, the coefficients of the interaction term should estimate zero. As shown in Table B1, the estimates are small and not statistically significant, except for bus usage. The effect of the early treatment on bus usage is negative (-0.0541), while the effect of the late treatment is positive (0.0208 = -0.0541+0.0759). However, neither of them is significant at the 5% significance level.

Table B1. Effects of the Early Treatment and the Late Treatment on Mode Usage

	1 subway	2 auto	3 bus	4 walk and bicycle
Treatment	0.0356**	-0.0503*	-0.0541*	0.0688**
	(0.0139)	(0.0299)	(0.0282)	(0.0277)
treatment x I (late treatment group)	-0.0198	-0.0181	0.0759**	-0.0380
	(0.0193)	(0.0391)	(0.0376)	(0.0350)
TAZ dummies	x	x	x	x
survey data dummies	x	x	x	x
district by year dummies	x	x	x	x
demographic variables	x	x	x	x
Observations	7,547	7,547	7,547	7,547

Notes: Standard errors are clustered at the TAZ level. *,**, *** indicate 10%, 5%, and 1% significance level, respectively.