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The Effects of Subway Expansion on Traffic Conditions

Evidence from Beijing

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The Effects of Subway Expansion on Traffic Conditions: Evidence from Beijing

Jun Yang, Shuai Chen, Ping Qin, and Fangwen Lu

Abstract

To alleviate traffic congestion, one of the most pressing urban challenges in developing countries, Beijing's government has been investing increasingly in subway infrastructure. In this study, using fine-scale daily traffic records from 2009 to 2013, we perform a regression discontinuity design to examine the average treatment effects of subway openings on traffic conditions in Beijing from 2009 to 2013. Three findings emerge from our empirical analysis. First, the opening of a new subway line resulted in a significant decline of daily passenger bus ridership, by 452,400 on average. Second, there was a significant positive impact on subway passenger ridership, with an average increase of daily passenger ridership by 246,300 after the opening of each new subway line. Third, we did not find any significant impact of new subway lines opening on the traffic congestion index, indicating that new subway openings have not effectively alleviated the traffic congestion in Beijing. Our results are quite robust to different tests. Our findings imply that subway construction might make it possible that car users give up vehicles and shift to the subway; however, this "pull" strategy alone is not enough to reduce congestion.

Key Words: subway construction, regression discontinuity, traffic congestion, public transportation

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The Effects of Subway Expansion on Traffic Conditions: Evidence from Beijing

Jun Yang, Shuai Chen, Ping Qin, and Fangwen Lu*

1. Introduction

Between 1990 and 2013, total population in Beijing increased from 6.995 million to 21.1 million. The built area in the city proper increased from 397 km^2 to 1,268 km,[2] and GDP per capita grew from 4,653 to 93,213 RMB during the same period. The rapid expansion and income growth were accompanied by a dramatic increase in vehicle ownership: the number of automobiles increased from 1.1 to 5.6 million from 2001 to 2014. Once a city of bicycle riders at the turn of the 21st century, Beijing now is routinely ranked as one of the most polluted and traffic congested cities in the world. To address traffic congestion, one of the most pressing urban challenges, the Beijing government has been investing heavily in public transportation infrastructure in recent years. It is expected that, by 2015, construction of a rail transit network with 279 stations and a total length of 561 kilometers will be finished in Beijing. Then, the network density within the 5th Ring Road[1] will reach 0.51 km/km^2, and every urban resident will be able to reach a subway station by walking for only about 1 kilometer.[2] Given the large investment in urban rail transit systems in Beijing, this paper aims to identify the effects of subway expansion on traffic congestion as well as subway ridership and bus ridership.

The craze for urban rail transit construction in Beijing can be partly explained by the belief that rail transit construction can reduce vehicle use and thus alleviate congestion. However, the potential benefits brought about by rail transit may be overestimated. Vickery

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[1] Beijing has a system of ring roads; the ring road nearest to the city center is the 2nd ring road, and the 6th ring road is the farthest away.

[2] Source: Action Plan for Green Transportation Construction in Beijing based on the Concepts of Humanism, Science and Environmental Protection (2009-2015).

indicated as early as 1969 that subway construction can reduce the use of vehicles by being an alternative means of commuting, but, at the same time, the improvement of traffic conditions may induce more commuting by vehicles. So, it is difficult to determine the exact impact of subway expansion on the use of vehicles. As a result, the ultimate impact of subway construction and expansion on urban congestion and air pollution is undetermined.

Although Beijing has been constantly building new lines in recent years, traffic congestion does not show significant improvement. The average driving speed on the road network of Beijing's downtown area during the morning peak was 26.4 km/h in 2011 and 26 km/h in 2012. This speed increased to 27.4 km/h in 2013, only a slight increase of 1 km/h compared with 2011.[3] This seems to suggest that the benefits from subway expansion in Beijing might not be as significant as expected by the government and public; however, mostly due to a lack of Chinese data, there is little empirical evidence of its magnitude. In this study, we perform regression discontinuity (RD) analysis to explore the relationship between subway opening and bus ridership, subway ridership, and, more importantly, the traffic congestion index in the Beijing central city area, taking advantage of a unique data set provided by the Beijing Transportation Research Center. With this econometric approach and unique data set, we believe we are able to alleviate several identification issues present in most previous literature. First, based on cross-sectional data, several studies investigate the effects of subway lines on travel behavior as well as on the associated congestion or air pollution by comparing commuting methods between a treatment group and a control group (Kain and Liu 1994; Petitte 2001). However, this method could be easily affected by self-selection bias because the residents who choose to live along the subway lines are more likely to prefer travel by subway. Moreover, the residents living near and further away from subway stations may differ in several dimensions such as income, age, educational background and vehicle ownership, which make these two groups unsuitable for comparison (Gordon and Willson 1984; West 2004; Feng et al. 2013). The second potential identification issue is simultaneity. The government may selectively choose to build subways in areas where the demand for automobile travel is relatively higher or the congestion situation is much worse, and hence congestion is likely to be elevated anyway. Such an endogeneity problem could pose a significant challenge to the credible estimates that are required to solve the identification issue. Third, to overcome the self-selection bias that is persistent in cross-sectional data, a difference-in-difference method can be used to explore the

[3] Data source: Beijing Transportation Research Center, 2013.

impact of subway construction on travel behavior (Xie 2012). Unfortunately, such studies are still not free from self-selection bias. The core of the DID method is to compare the differences between the treatment group and the control group before and after the policy shock. The rationale for such an approach is that the time trend of the two groups should be consistent. When there is no treatment group (the subway is either operating or not), there is no hypothetical treatment group that could accurately measure the true causality effects related to the policy (or shock). Therefore, these estimates are bound to raise arguments and doubts.

In light of these concerns, we use the RD method to estimate the marginal treatment effects of the subway opening on public transportation ridership and traffic congestion. This analysis was performed based on the following assumption: the opening date of the new subway line was taken as the threshold; if there was no other transportation policy introduced before or after this opening date (within the sample range) – or if there was, but the observables or unobservables could affect the dependent variables smoothly in the neighborhood of the subway opening date – then, the occurrence of the discontinuity point in the regression could be attributed to the opening of the new subway line. The central assumption of this approach is that the dependent variables should change smoothly over time-series observations around the opening day threshold. In order to isolate the change in dependent variables solely due to the opening of new subway lines, polynomial time trends are usually used to control for non-linear effects arising from other confounding factors (see, for example, Gibbon and Machin 2005 and Davis 2008).

We studied the average treatment effects of the five new subway lines that operated during 2009-2013 in Beijing. Three findings emerge from our empirical analysis. First, a significant and negative impact was found on bus passenger ridership. On average, the opening of each new subway line resulted in a decline of daily bus ridership by 452,400. Second, there was a significant positive impact on subway passenger ridership, with an average increase of daily ridership by 246,300 after the opening of each new subway line. Third, we did not find significant impact of new subway lines on the traffic congestion index, including the all-day average index, morning peak index and evening peak index. We also conducted a series of robustness tests, i.e., a number of alternative specifications, including different samples and randomly chosen thresholds. The results are quite robust to these tests.

We speculate on two possible explanations for why subway expansion did not effectively alleviate the traffic congestion. First, it might be that a new subway opening diverts riders mostly from buses or even generates new riders from those who walked or rode bicycles. In such cases, subway expansion is not a substitute for vehicles. Second, even if subway expansion has a

substitution effect on vehicles, the improvement of traffic conditions might induce more commuting by vehicles. Consequently, the roads are still as congested as before.[4] Though subway construction makes it possible for car users to give up the car and transfer to the subway system, the evidence of our study demonstrates this "pull" strategy alone is not enough.

Our study offers the following contributions. First, it facilitates a better understanding of the contradictions and challenges encountered during the simultaneous process of motorization and urbanization taking place in large and medium-sized cities in China. In the early stage of China's motorization, the government failed to take actions to inhibit the explosive growth of vehicles, which led to the phenomenon of a larger vehicle population in the more densely populated areas. This seriously violates good practices of motorization development of large cities in other parts of the world. During a motorization process that is not planned or regulated, vehicles are intensively used within distances that can be covered by bus or walking. This directly results in unnecessary traffic congestion and air pollution (Li 2014; Yang et al. 2014; Li et al. 2014; Sun et al. 2014; Xie 2012).

Second, our research can also contribute to the design of effective transportation policies to control traffic congestion in other Chinese cities. Currently, some second-tier and third-tier cities and even a few counties in China are also constructing their first subway lines. At present, 38 cities have been approved by the central government to construct at least one subway line before 2020 (Dong and Wu 2013). It is estimated that, by 2020, the mileage of China's rail transit will reach 6000 kilometers, accounting for over 40% of the total mileage of rail transit in the world. The total investments in rail transit will approach 4,000 billion RMB.[5] Therefore, whether as an experience or a lesson, the efforts made by Beijing to reduce traffic congestion through a shift to green transportation, with subway expansion as the focus, can be referred to by those cities.

Third, our work adds to the rich literature that identifies the effects of public transport on traffic congestion alleviation. In the existing literature, no consensus is reached on the alleviating

[4] Because data on vehicle flow is unavailable, these two possibilities cannot be further analyzed. Analyzing data from a household survey of Beijing residents' travel in 2007-2009, Xie (2012) found that subway use increased by 98.3% and vehicle use decreased by 19.8% after subway expansion. This result supports the substitution effect of the subway on vehicles. Based on this analysis, the second explanation is more likely to be true.

[5] Data source: A Bird's-Eye View on Metros, Metrobits: http://mic-ro.com/metro/metrostats.html.

effect of public transport infrastructure, and most work is done in developed countries. For example, Anderson (2014)[6] used a regression discontinuity design to study a sudden strike in 2003 by Los Angeles transit workers. He found that the average highway delay increases 47% when transit service ceases. This in turn demonstrates that the net benefits of transit systems appear to be much larger than previously believed. Nelson et al. (2007) estimated the travel benefits of the local transit system to transit users and the congestion-reduction benefits to motorists in the Washington, D.C., metropolitan area, using a simulation model in which travel decisions are modeled as a nested logit tree. They calculated that the Washington transit system reduces total congestion by 184,000 person-hours per day, or 2.0 person-minutes per peak transit passenger mile carried. On the other hand, using metropolitan-area data, Winston and Langer (2006) estimated that, although rail lines reduce congestion, bus lines increase congestion; the net effect of transit systems is thus to increase congestion. Duranton and Turner (2011) investigated the relationship between interstate highways and highway vehicle kilometers traveled (VKT) in US cities and estimated a positive relationship between bus fleet size and vehicle miles traveled (VMT). They concluded that increased provision of roads or public transit is unlikely to relieve congestion.

The remainder of the paper is organized as follows. Section 2 provides an overview of Beijing's subway development. Section 3 presents the empirical framework and data. Section 4 discusses the empirical results. Section 5 provides robustness tests and Section 6 concludes.

2. Subway Development in Beijing

Before 2000, there were only two subway lines (Line 1 and Line 2) in Beijing. Line 1, completed in 1969, is the first subway line in China, by which Beijing's downtown area, Chaoyang District and western suburbs were connected. In 2004, Line 1 was extended at the eastern section by the newly built Batong Line, which connects with the Tongzhou District in the eastern suburbs. Line 2 was first operated back in 1987; it is a loop line in Beijing. Built along the old urban district of Beijing, Line 2 overlaps with the Second Ring Road in the eastern, northern and western sections. In the following 15 years, no new subway lines were built in

[6] The magnitude of the effect of ceasing operation of a subway or line and that of opening a subway or line may be asymmetric. One reason is that commuters need time to adjust to the changes. So, the magnitude of the effects of ceasing subway operation is likely to be more similar to the long run effects of opening a subway than to the effects we study at the discontinuity.

Beijing. It was not until 2002 that another subway line, Line 13, began operation. This line starts from Xizhimen Station in the west and ends in Dongzhimen Station in the east, with a total distance of 40.5 kilometers and 16 stations.

As part of the preparations for the 2008 Olympic Games, the Beijing government invested heavily in the construction of subway infrastructure. At least one subway line has been added every year since 2007. The development of the Beijing subway after 2007 is unprecedented around the world. Beijing's investments in transportation infrastructure from 2007 to 2013 exceeded RMB 300 billion. Twelve subway lines and one airport express were constructed, with an increase of operational mileage by 351 kilometers. Moreover, another 12 subway lines are currently under construction and will be opened in late 2015. By then, the total operational mileage of Beijing subways will approach 561 kilometers.

In this study, nine subway lines opened in 2009-2013 are investigated. These are Line 4, Line 15 (Phase 1), the Changping Line (Phase 1), the Daxing Line, the Fangshan Line, the Yizhuang Line, Line 9, Line 6 and Line 14; see Fig. 1. Line 4 was put into operation on September 28, 2009, facilitating north-south transport in western Beijing. The total length of Line 4 is 28.2 kilometers, with a total of 24 stations (see Table 1). Line 15 (Phase 1), the Changping Line (Phase 1), the Daxing Line, the Fangshan Line, and the Yizhuang Line opened at the same time; they link the new towns in the suburbs, with a total distance of 122.4 kilometers and 54 stations. Line 9, opened on December 31, 2011, is the longitudinal trunk in western Beijing. It intersects with Line 4, Line 6, Line 1 and the Fangshan Line, with a total distance of 16.5 kilometers and 13 stations. Line 6 (Phase 1), opened in December 2012, is a transmeridional trunk running through the central city. Its total distance is 30.4 kilometers with 20 stations. The western section of Line 14 was put into operation in May 2013, with a total distance of 12.4 kilometers and 7 stations. The completed Line 14 will be an L-shaped line that connects the northeast and the southwest. By May 2013, the total mileage of the five lines was 210 kilometers, accounting for 45% of the total operational mileage (465 kilometers) of the Beijing subway. The distribution of the five subway lines in relation to the ring roads in Beijing is shown in Fig. 1.

3. Empirical Framework

3.1 Regression Discontinuity Design

This study estimates the average marginal treatment effect of the opening of new subway lines on public transportation, with a focus on the impact of new lines opening on traffic

congestion in the Beijing central city area. A sharp regression discontinuity design is used for this estimation strategy. According to Angrist and Pischke (2008), when there is only one discontinuity point of intervention, the local average treatment effect (LATE) β_1 can be estimated using the equations below:

$$BPV_t = \beta_0 + \beta_1 Treat_t + \beta_2 f(X_t) + \varphi Z_t + \varepsilon_t \quad (1)$$

$$SPV_t = \beta_0 + \beta_1 Treat_t + \beta_2 f(X_t) + \gamma Z_t + \upsilon_t \quad (2)$$

$$TCI_t = \alpha_0 + \alpha_1 Treat_t + \alpha_2 f(X_t) + \phi Z_t + u_t \quad (3)$$

where BPV_t and SPV_t are the bus and subway passenger ridership, respectively, on the *t*-th day. TCI_t represents the congestion index on the *t*-th day (including the congestion index during the morning and evening peak, as well as the average daily congestion index). $Treat_t$ is the dummy variable indicating whether or not the new subway line is open on the *t*-th day; 0 indicates not open while 1 indicates already open. X_t is the number of days from the date of the new subway line opening to the *t*-th day, characterizing the time between the sample point and the discontinuity point. Here we call X_t the predictor. Before the opening of the new subway line, X_t takes a negative value; after the opening, X_t takes a positive value; on the day of opening, X_t is denoted as zero. $F(X_t)$ is the *k*-th order polynomial function, used to flexibly control for time-series variation in the passenger ridership or congestion that would have occurred in the absence of the opening of the subway lines. Z_t represents other control variables, including the dummies such as extreme weather, weekday and holiday.

Some estimation details need to be discussed here. Firstly, to use RD design to evaluate the causal effect of new subway lines opening, one central assumption is that the observables or unobservables affect the dependent variables smoothly in the neighborhood of the subway opening date. Therefore, in the regression equation, we use a higher-order term of X_t to control for the non-linear effect of the unobservable factors on outcome variables. Secondly, an important issue in practice is the selection of the smoothing parameter, the bandwidth *h*. When we use a nonparametric estimation approach, the variation range of the forcing variable X_t is divided into K bins according to a certain bandwidth *h*. Subsequently, the outcome variable in each bin is simulated piecewise (Imbens and Lemieux 2008). Generally, the range of the bin should not be too narrow or too wide. If bins are too narrow, the estimates will be highly imprecise. In practical terms, the problem is that, in finite samples, the bandwidths have to be

large enough to encompass enough observations to get a reasonable amount of precision in the estimated values of treatment effects. If they are too wide, the estimates may be biased because they fail to account for the slope in the regression line, which is negligible for very narrow bins (Lee and Lemieux 2010). The estimation method in our study is local polynomial regression. In practice, a cross-validation procedure is recommended to determine the optimal bandwidth (Imbens and Lemieux 2008). Third, in order to ensure the effectiveness and robustness of the estimation, a series of robustness tests was conducted, including different higher-order terms, bandwidths, samples and length of the sample. Fourth, due to the lack of detailed data concerning the use of vehicles and taxis, the degree of the substitution effect on different commuting methods induced by opening of the new subway line cannot be analyzed precisely. Here, by analyzing the impact on traffic congestion and on bus and subway passenger ridership, we limit our further exploration to the possibility of replacing car trips with commuting by subway.

3.2 Data Description

Our data include daily passenger trips by bus and subway as well as the traffic congestion index for the central city in Beijing from August 2009 to July 2013. The date when the subway line of interest was opened during this period was taken as the discontinuity point. With each discontinuity point as the origin, the relevant data 60 days before and after the opening of each subway line were observed, and therefore a total of 605 observed values were obtained for the five batches of subway lines opened during this period. We decided to use 60 days before and after the opening of the subway as the sample period to ensure no overlap between the sample periods of each subway line. For example, the sample periods of Line 6 and Line 14 were very close, but there was no overlap. The last day of the sample period after the opening of Line 6 was February 28, 2013, while the first day of the sample period of Line 13 was March 6, 2013. Detailed information concerning the subway samples is shown in Table 1.

The daily passenger ridership of bus and subway data was from Beijing Daily Transport Operation Monitoring, released by the Transport Operation Control Center of Beijing. The daily traffic congestion index (TCI), as the measure of motorized traffic speed in Beijing's central city, is provided by the Beijing Transportation Research Center.

TCI[7] is an aggregated index of road congestion that is calculated using real-time speed and location of 40,000 floating cars within the 5th Ring Road, weighted according to traffic volumes of each road link. The index describes the relationship between travel time according to real-time speeds on the road and travel time in obedience to the road's speed limit (Zhong 2015). TCI is scaled between 0 and 10, with 0 meaning no congestion at all and 10 referring to complete congestion. The available TCI data[8] covers morning and evening peak traffic and daily average traffic between August 2009 and July 2013.

In addition, we are concerned with extreme weather that may affect the commuting choices. Our analysis focuses on five types of extreme weather: heat wave, cold spell, rainstorm, gale and snow. The definitions of these extreme weather conditions were based on meteorology.[9] High temperature and heat wave usually refer to weather with air temperature higher than 35°C for several consecutive days. A cold spell is defined as a rapid fall in temperature by over 8°C within 24 hours (or a fall by over 10°C within 48 hours) when cold air passes through a region and the lowest temperature declines to below 4°C. Rainstorm refers to heavy rain with precipitation of 50 mm or above within 24 hours. Meteorologically, gale refers to a wind of Grade 8 strength, with wind speed of 17.2-20.7 m/s. Snow is defined as snowfall of 1.0-3.0 mm within 12 hours, snowfall of 2.5-5.0 mm in 24 hours, or snow depth reaching 3cm.

Information about official holidays and off-duty shifts was obtained from the notice of yearly holiday arrangements released by the General Office of the State Council and arranged by the authors. The statistical information about the variables discussed above is shown in Table 2.

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[7] The team that designed and implemented TCI includes the Beijing Transportation Research Center, Beijing Jiaotong University, and ERTICO, which stands for ITS Europe, the network of Intelligent Transport Systems and Services stakeholders in Europe. Since 2010, the TCI has been formally incorporated into national standards and has become a set of normative guidance documents.

[8] For example, Sun et al. (2014) used the traffic congestion index to quantify driving restrictions' effects on traffic. They found a significant and positive impact on traffic congestion with the driving restriction program. Using TCI data and leveraging the variation in the last digit of vehicles' license plate numbers, Zhong (2015) found that traffic congestion is 20% higher on days when the vehicles with license plate numbers ending in 4 and 9 are banned.

[9] http://baike.baidu.com/.

4. Empirical Results

Based on equation (1), we used the RD method to estimate the marginal effect on bus ridership of the new subway line opening. The estimation results are reported in Table 3. In column 1, we include only the dummy variable indicating the opening of the new subway line, the first order term of the forcing variable X_t, and their interaction terms. The estimated coefficient of the variable $Treat_t$ is of the most interest. The estimated average treatment effect is -0.7748, suggesting a decline of daily bus passenger ridership by 774,800 on average with the opening of each new subway line.

Column 2 considers the spatial factors. The regression was estimated with the number of stations of each subway line as weights. In order to flexibly control nonlinearities from other factors in outcome variables, a fifth-order polynomial time trend and its interaction with the dummy for the opening of the subway line were further included in column 3. Column 4 was the final benchmark model, in which day of the week dummy and holiday dummy are included to control for unobserved temporal factors and weather dummies. In all model specifications, standard errors were clustered at the date level to account for possible serial correlation with days of the week.

The results indicate that, in all model specifications, the average treatment effect with the opening of the new subway line was always negative and significant at a 1% confidence level. However, the magnitude of estimated coefficients gradually decreased to -0.4524 in the final model specification. If we focus our discussion on the final model specification, the results show, on average, a decline of daily bus trips by 452,400 in Beijing with the opening of each new subway line.

Based on the above model specification to estimate the impact on bus ridership, we estimated the average treatment effect on subway ridership and on the traffic congestion index (including the daily TCI and the TCI during the morning peak (MP) and evening peak (EP). The final results are shown in Table 4. For simplicity, only the estimated $Treat_t$ dummy variable is listed in the table. In column 2, we show that the estimated average treatment effect of the subway line opening on subway ridership gradually increased with the addition of control variables in the model. In the benchmark model 4, the estimated parameter was positive and significant at a 1% confidence level, suggesting that, after the opening of the five subway lines, the average growth of daily ridership associated with each subway line was 246,300.

Columns 3, 4 and 5 report the estimated treatment effect of new subway lines on the daily TCI, morning peak TCI and evening peak TCI, respectively. We found that the estimated

parameters are negative, but insignificant for all three congestion indices, except for the morning TCI in model specifications 1 and 2. This suggests that the opening of subway lines had a significant and negative effect on bus ridership and a significant and positive effect on subway ridership, but no significant effect on traffic congestion.

The above findings are also presented graphically in Figs. 2 and 3. Figure 2 and Figure 3 plot daily bus passenger volume (BPV also means ridership) and subway passenger volume (SPV also means ridership) against a predictor variable that indicates the ordinal number of days from the opening of a new subway line.[10] The line is the fitted value of BPV and SPV from the estimation of RD regression in local linear fashion (left) and polynomial fashion (right). The obviously discontinuous decline in BPV and increase in SPV around the opening date of a new subway line was observed in the right-hand figure. The plots also suggest that the opening of the new subway line decreased bus ridership and increased subway ridership.

To sum up, our results indicate that the central city traffic congestion situation cannot be effectively alleviated by subway construction alone. There are two possible reasons. First, subway has a substitution effect on bus travel, but possibly not on private cars. Thus, there is no obvious improvement of traffic conditions. Secondly, subway expansion may exert a substitution effect with respect to private cars and thereby slightly improve traffic conditions, which in turn induces more commuting by private cars. Hence, the traffic congestion remains unchanged.

The above analysis is partly supported by the Beijing Household Travel Survey (BHTS) in 2010[11]. According to this survey, the use of private cars reached 60% in daily commuting for families who own a car in Beijing. This proportion was much higher than the average level of 20%-30% in other comparable cities in the world. In addition, based on data regarding vehicle type composition[12] (shown in Table 5), we can further discuss how private cars contribute to traffic volume. As shown by these statistics, based on traffic flow observation, the proportions of cars, taxis and buses used in road transport on one day in 2011 were 58%, 17% and 10%, respectively. In 2013, the proportion of cars increased rapidly to about 64%, and that of taxis and

[10] Here we use plus and minus to indicate the direction. Plus indicates days after subway opening date, and minus indicates days before it.

[11] The BHTS survey was conducted in September and October 2010 by the Beijing Transportation Research Center (BTRC). Holiday periods in those two months (Sept. 22-24 and Oct. 1-7) were excluded. All sample respondents were interviewed face-to-face in their homes and asked to report their travel in a one-day trip diary. A total of 46,900 households and 116,142 individuals were interviewed.

[12] This data was provided by the Beijing Transportation Research Center.

buses decreased to 13% and 5%, respectively. Hence, we can conclude that the use of private cars contributed considerably to traffic congestion, and that the contribution rapidly increased year by year.

On this basis, the reason for the poor substitutability of the subway for private cars was further explored. Table 6 reports the features of the main commuting modes obtained from the Beijing Household Travel Survey in 2010. Compared with rail transit, the travel speed of cars is only slightly higher, with an average speed of 17.7 km/h; the travel distance is relatively short, with an average of 11.5 km. However, it is worth noting that the cost of commuting by private car is extremely low. It is merely 0.7 yuan/km when only considering road tolls and parking fees, while the commuting cost of rail transit is 0.14 yuan/km. Even if the fuel cost is taken into consideration, the average cost of commuting by private cars is 0.72 yuan/km, only (roughly) five times the subway cost per km.

On the other hand, the lower land use intensity around the Beijing subway stations and the poor transfer interfaces restrict the subway's attraction. The average plot ratio[13] within a range of 3 km around subway stations in Beijing is only one-fourth of that in Tokyo, and this means poorer population coverage and attraction (Zhou 2015). Most of the subway stations in Beijing are located within the central city, which was already built up before subway construction. More effort, time and money are needed to coordinate efforts if the government wants to set up stations and entrances in the high-population land plots. Facing limited resources, the government had to "stick in a pin" wherever there was room, with the result that subway stations were placed in green spaces and at urban expressway curbsides. Such places are often land plots with low population density.

Meanwhile, the subway travel experience in Beijing still needs to be improved. The 2010 BHTS shows the average out-of-subway time in one subway trip, including walking time and waiting time, was about 26.3 minutes, accounting for 44% of the whole travel time. In addition, subway cars are packed like sardines, especially at peak times. The Beijing Transportation Research Center has announced that the load factors of 75% of the subway lines exceeded 100% at peak times.[14] Compared with the poor subway travel experience, the cost of using a car is

[13] Plot ratio is an urban planning term. It is the ratio of built area to land area. A higher plot ratio indicates higher land use intensity.

[14] http://news.xinhuanet.com/yzyd/local/20140708/c_1111504211.htm

quite low considering its travel speed, convenience, comfort, and privacy. Therefore, we speculate that the fairly low cost of using cars, especially the low parking fees, may be one major reason why the subway cannot attract more car users.

5. Robustness Checks

In this section, we examine the robustness of our results according to several different tests to confirm whether the results were affected qualitatively by the decisions made in our paper along several dimensions, such as bandwidth choice, sample length, sample selection, and functional forms of our models.

5.1 Robustness Check for Various Bandwidths

The parameter estimation for regression discontinuity analysis was performed under a certain bandwidth. This brings up the concern of whether the results could be sensitive to the bandwidth choice. Hence, the robustness of the results for various bandwidths was first tested.[16] With the optimal bandwidth obtained by a cross-validation procedure, we investigated the inference sensitivity to bandwidth by setting it at 50%, 75%, 125%, 150%, 175% and 200% of the optimal bandwidth, respectively. The result is shown graphically in Figures 4, 5 and 6. Figure 4 reports the regression results of daily bus and subway ridership under different bandwidths. The results show that the treatment effects estimation is highly robust in different scenarios, except for the case of 50% of optimal bandwidth. Figure 5 reports the regression results of the daily TCI under different bandwidths and Figure 6 reports the results of the morning and evening peak TCI, respectively. The results were similar to those for bus and subway ridership. Therefore, we can conclude that our results hold when we choose different bandwidths, except for 50% of optimal bandwidth.

5.2 Robustness Check with Alternative Polynomial Orders

In our nonparametric estimation with local polynomial regression, we choose the 5th order term of the forcing variable X_t as one of the dependent variables. This section investigates the robustness of estimation results by choosing other, higher polynomial orders. Table 7 shows

[16] Lee and Lemieux (2010) indicated that it is necessary to test the robustness of results under different specifications of bandwidth *h*.

the estimation results where the 5th, 6th, 7th and 8th order polynomials of X_t, respectively, were controlled based on the benchmark model specification. The results are highly robust among different polynomial orders. It is noteworthy to mention that the estimation coefficients of the traffic congestion index were still not significant.

5.3 Robustness Check for Alternative Sample Set

In this section, the samples were re-divided and re-estimated using two kinds of robustness checks. First, the sample data around the opening date of each subway line was considered as an independent sample set. Second, we eliminated the sample sets that could be affected by transportation policies other than subway opening. There were two important transportation policies introduced in Beijing in our study period. One was a car registration lottery policy for curbing the total number of cars, beginning on January 1, 2011; the other was an adjustment of taxi fares on June 10, 2013. As the two points in time fell within our sample period, the estimation results may be affected. So, we eliminate the sample data around the opening dates of Line 15 (October 30, 2010) and Line 14 (May 5, 2013), and we re-estimate the model. The comparison of estimation results for different sample sets is presented in Table 8.

The results of the regression indicate that the opening of each new subway line still had a significant impact on bus and subway ridership, with the sign of the coefficient as expected. Moreover, all the marginal effects estimates on the congestion index were insignificant under all model specifications, except that the marginal effect of Line 14 on the traffic congestion index during morning and evening peaks showed slight significance, at the 10% confidence level.

After the elimination of the data for Line 15, Line 14, or both, the estimation results of the ridership of bus and subway were all significant. The sign of the coefficient was the same as expected. The coefficient estimates of the congestion index were all insignificant and negative, with the results slightly higher than those under the benchmark condition. In general, the results of regression estimation remained robust under alternative sample sets.

5.4 Robustness Check at Non-discontinuity Points

As a robustness check of RD design, estimating jumps at points where there should be no jumps is highly recommended (Imbens and Lemieux 2008). We further perform robustness tests by artificially choosing cutoffs, which include cutoff 1 at -5 days (5 days before the original point); cutoff 2 at 5 days (5 days after the original point); cutoff 3 at -10 days (10 days before the original point); and cutoff 4 at 10 days (10 days after the original point). The estimation results

under different configurations of cutoffs are presented in Table 9. In general, the results show that there are no significant jumps at non-discontinuity points. As to the TCI, only the coefficient estimates of the evening peak TCI under the configuration of cutoff 1 and the morning peak TCI under the configuration of cutoff 3 were significant and negative. Therefore, we believe that the estimation results were basically robust under different configurations of the cutoffs.

5.5 Robustness Check for Various Time-window Lengths of the Sample Data

In the benchmark regression, we chose 60 days before and after the subway line opening date as a time-window length. Here, we change the time-window length of the samples for regression discontinuity analysis under the benchmark model, and perform the robustness check by comparing the estimation results. The samples spanning both 30 and 90 days before and after the discontinuity point were chosen for estimation (see Fig. 7). It can be seen from Fig. 7 that the negative impact on bus passenger ridership and the positive impact on subway passenger ridership still exist for various time-window length sample data. This shows the results' robustness for sample data covering time windows of various lengths.

5.6 Robustness Check with One Particular Subway Line

We now assess the robustness of our results by looking at the effect on traffic congestion of only one subway line opening. Ideally, we want information on the traffic congestion index from one road network to conduct this analysis. However, this type of data is not available. We instead use the road speed data from Liangguang Street to proxy for the degree of traffic congestion. The road travels from east to west, with around 8.4 km of its length parallel to Line 7, which opened at the end of 2014. We chose 90 days before and after the Line 7 opening date as the time-window length. The regression results are presented in Table 10. Our results demonstrate that there was no significant speed improvement on the Liangguang road network with the opening of Line 7.

6. Conclusion

As an international metropolitan area under rapid development, Beijing is facing a sharp rise in its vehicle population. While its residents have enjoyed great benefits from this increase in mobility, they and their neighbors are also paying a heavy price. Beijing has been named by numerous international organizations as one of the most gridlocked cities in the world. The city is also one of the world's most polluted cities in terms of air quality, and vehicular emissions contribute heavily to hazardous air pollutants. In order to deal with these challenges, Beijing has

invested heavily in public transit infrastructure. According to the Plan for Beijing's Rail Transit Construction (2011-2020), there will be 30 subway lines constructed by 2020, with around 450 stations and the total length reaching 1,050 kilometers. Although the Beijing government believes that the expansion of urban rail transit can reduce congestion, pollution and energy consumption, the potential benefits brought about by rail transit may be overestimated under actual conditions in Beijing.

We estimate the average treatment effect on bus and subway passenger ridership and daily congestion indices in Beijing by exploiting the rapid expansion of the subway networks in recent years. Based on daily passenger ridership information and daily congestion index data, we use RD design to estimate the impact of the opening of new subway lines on bus and subway ridership and on the traffic congestion index. We also use a higher order polynomial function to flexibly control for time-series variation in the ridership or congestion that would have occurred in the absence of the opening of the subway lines.

We have three major findings. First, a significant and negative impact was found on bus ridership. On average, the opening of each new subway line resulted in a decline of daily bus ridership by 452,400. Second, there was a significant positive impact on subway ridership, with an average increase of daily ridership by 246,300 after the opening of each new subway line. Third, we did not find a significant impact of new subway lines opening on the traffic congestion index, including the all-day average index, morning peak index and evening peak index. Though subway construction makes it possible for car users to give up driving and transfer to the subway system, our study demonstrates that this “pull” strategy alone is not enough.

We speculate that the low cost of private vehicle use is the main reason that the rapid expansion of the subway network in Beijing is not effective in reducing traffic congestion. Given the poor transfer service of the subway system and the crowding of subway cars, especially at peak times, "door-to-door" commuting using private cars is generally superior to rail transit in terms of travel speed, comfort, and privacy. In addition, the low cost of private vehicle use makes it competitive with the subway. According to the 2010 Beijing Household Travel Survey, the average cost of commuting by private cars was 0.72 yuan/km, only (roughly) five times the subway cost per km.

It is difficult to attract vehicle owners to give up driving and commute by subway. Therefore, to reduce traffic congestion, the vigorous development of public transport in Beijing should be combined with an increase in the cost of using private cars. Otherwise, the potential benefits from public transport investment will be greatly reduced. For example, some work has

shown that vehicle users are fairly sensitive to parking fees. The study by Shoup (2011) in Los Angeles found that 70% of the commuters would go to the office by private cars when there was free parking. However, when the parking fee increased to US $5, the proportion declined to 43%, and the commuters choosing public transport increased markedly. In Beijing and nearly all the cities in China, free parking is a very common phenomenon. Therefore, it is recommended for Beijing and other Chinese cities that parking fees be imposed or increased. Combining with the pull strategy of subway construction, this pull-and-push policy will not only increase the benefits of subway construction, but also facilitate the shift of commuting modes from private cars to subway.

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Tables and Figures

Table 1. Sample Subway Lines and Selection of Sample Period

Subway Lines	Date	Sample Period	Stations	Length(km)	Holidays
Line 4	Sep. 28, 2009	08/17/2009-12/15/2009	24	28.2	8
Line 15	Dec. 30, 2010	10/31/2010-02/28/2011	54	122.4	10
Line 9	Dec. 31, 2011	11/01/2011-02/29/2012	13	16.5	10
Line 6	Dec. 30, 2012	10/31/2012-02/28/2013	20	30.4	10
Line 14	May 5, 2013	03/06/2013-07/04/2013	7	12.4	9

Notes: Total sample *N*=605. We choose 60 days before and after subway line opening (cutoffs) respectively, which include 121 days for each subway line. Holidays exclude weekends.

Table 2. Summary Statistics

Variable	Unit	Mean	SD	Min	Max
Bus Passenger Volume (BPV)	Million	13.274	1.757	5.463	15.800
Subway Passenger Volume (SPV)	Million	6.278	1.868	1.321	10.370
Traffic Congestion Index (TCI, Daily Average)	0-10	4.568	1.856	1	8.550
Traffic Congestion Index (TCI, Morning Peak)	0-10	3.639	2.064	0.800	9.300
Traffic Congestion Index (TCI, Evening Peak)	0-10	5.450	2.141	1	9.300
Holiday	(0, 1)	0.078	0.268	0	1
Extreme Weather	(0, 1)	0.035	0.183	0	1

Note: N=605. Other variables in our research include dummies for weekdays and subway lines, respectively. For brevity, they are not reported here. Holiday excludes weekends; extreme weather includes *heat wave, cold spell, rainstorm, gale and snow*, based on meteorological definitions at Baidu Encyclopedia (http://baike.baidu.com/).

Table 3. Sharp RDD: Model Specifications (1)-(4)

Model Specification	(1) BPV	(2) BPV	(3) BPV	(4) BPV
Treat	-0.7748***	-0.7501***	-0.6984***	-0.4524***
	(-6.27)	(-7.04)	(-5.73)	(-6.16)
Predictor	-0.0105**	-0.0135***	-0.0120***	-0.0086***
	(-3.50)	(-6.15)	(-3.93)	(-6.13)
Interaction	0.0017	0.0007	0.0012	-0.0085**
	(0.35)	(0.19)	(0.34)	(-3.03)
Holiday				-3.5946***
				(-8.14)
Extreme weather				-0.3179
				(-1.73)
Weighted by stations	No	Yes	Yes	Yes
Polynomial in Time trend	No	No	Yes	Yes
Covariates	No	No	No	Yes
_cons	13.6385***	13.4704***	13.2839***	14.1002***
	(63.19)	(55.53)	(79.89)	(114.29)
N	605	605	605	605
R^2	0.158	0.194	0.288	0.724

Notes: "Polynomial in Time trend" controls 5th order polynomial in predictor; "Covariates" contain both weekday dummies and subway lines dummies as extra control variables; *Std. Err.* adjusted for 7 clusters for the seven days of the week; *t* statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. SRD: Baseline Regressions Relative to Model Specification (1)-(4)

	BPV	SPV	TCI(DA)	TCI(MP)	TCI(EP)
Panel 1 Local Linear Estimation					
Treat	-0.7748***	-0.0449	-0.4269	-0.4706*	-0.4577
	(-6.27)	(-1.83)	(-1.66)	(-2.00)	(-1.70)
R^2	0.158	0.001	0.098	0.054	0.113
Panel 2 Add Weighted Regression by Stations					
Treat	-0.7501***	0.0724	-0.6050	-0.7794*	-0.5876
	(-7.04)	(1.84)	(-1.52)	(-1.95)	(-1.67)
R^2	0.194	0.002	0.182	0.107	0.212
Panel 3 Add Higher-order Polynomial in Predictor					
Treat	-0.6984***	0.0974	-0.5506	-0.7561	-0.5061
	(-5.73)	(1.42)	(-1.43)	(-1.92)	(-1.55)
R^2	0.288	0.533	0.254	0.151	0.333
Panel 4 Control Holiday, Weekday, Extreme Weather and Subway Lines					
Treat	-0.4524***	0.2463***	-0.3219	-0.5322	-0.2707
	(-6.16)	(4.22)	(-0.99)	(-1.53)	(-0.91)
R^2	0.724	0.806	0.707	0.697	0.679

Notes: N=605; Panels (1)-(4) correspond to model specifications (1)-(4); *Std. Err.* adjusted for 7 clusters for the seven days of the week; *t* statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Composition of Traffic Flow from 2011-2013

Year	Car (%)	Taxi (%)	Bus (%)	Others (%)	Total
2011	58.29	16.90	9.61	15.19	100
2012	62.45	14.03	8.60	14.92	100
2013	64.18	13.38	5.24	17.21	100

Data Source: Beijing Traffic Flow Check Survey, 2011-2013. The Beijing Transportation Research Center selected more than 300 observation points within the 5th Ring Road, and conducted a one-day traffic flow observation survey.

Table 6. Characteristics of Different Travel Modes

Mode	Distance (km)	Time (mins)	Velocity (km/h)	Cost (RMB/km)
Car	11.5	38.9	17.7	0.07
Subway	18.0	77.3	14.0	0.14
Bus	10.8	65.4	9.9	0.06
Taxi	9.3	39.2	14.2	2.43

Data Source: Beijing Household Travel Survey, 2010.

Table 7. Robustness Check: nth order Polynomial

	BPV	SPV	TCI(DA)	TCI(MP)	TCI(EP)
5*th* order Polynomial (Baseline)					
Treat	-0.4524***	0.2463***	-0.3219	-0.5322	-0.2707
	(-6.16)	(4.22)	(-0.99)	(-1.53)	(-0.91)
R^2	0.724	0.806	0.707	0.697	0.679
6*th* order Polynomial					
Treat	-0.4511***	0.2466***	-0.3534	-0.5440	-0.3245
	(-6.10)	(4.05)	(-1.07)	(-1.53)	(-1.05)
R^2	0.724	0.806	0.717	0.698	0.700
7*th* order Polynomial					
Treat	-0.4782***	0.2530***	-0.3972	-0.5941	-0.3660
	(-6.24)	(4.06)	(-1.13)	(-1.57)	(-1.12)
R^2	0.725	0.807	0.720	0.702	0.702
8*th* order Polynomial					
Treat	-0.4641***	0.2210***	-0.3616	-0.5421	-0.3421
	(-6.03)	(3.74)	(-1.03)	(-1.47)	(-1.02)
R^2	0.725	0.809	0.721	0.704	0.702

Notes: N=605; regression based on model specification (4); *Std. Err.* adjusted for 7 clusters for the seven days of the week; t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. Robustness Check: Subsample Regressions

	BPV	SPV	TCI(DA)	TCI(MP)	TCI(EP)
Subway Line 4 (Sept. 28, 2009)					
Treat	-0.2789*	0.4539***	-0.5303	-0.8148*	-0.2443
	(-1.76)	(4.83)	(-1.06)	(-2.34)	(-0.35)
N	121	121	121	121	121
R^2	0.680	0.665	0.699	0.732	0.562
Subway Line 15 (Dec. 30, 2010)					
Treat	-0.1490	0.5079***	-0.5896	-1.0014	-0.5197
	(-1.04)	(5.40)	(-0.99)	(-1.74)	(-0.85)
N	121	121	121	121	121
R^2	0.690	0.638	0.778	0.739	0.783
Subway Line 9 (Dec. 31, 2011)					
Treat	-0.8554***	0.0288	-0.3614	-0.6965	0.0333
	(-5.57)	(0.25)	(-1.10)	(-1.43)	(0.07)
N	121	121	121	121	121
R^2	0.701	0.725	0.709	0.700	0.699
Subway Line 6 (Dec. 30, 2012)					
Treat	0.0486	1.0750***	-0.1808	-0.1995	-0.1013
	(0.43)	(6.28)	(-0.24)	(-0.26)	(-0.13)
N	121	121	121	121	121
R^2	0.854	0.804	0.712	0.643	0.665
Subway Line 14 (May 5, 2013)					
Treat	-0.5828**	-0.1982	-0.5163	-0.2835	-0.6805
	(-2.88)	(-0.67)	(-0.94)	(-0.48)	(-1.24)
N	121	121	121	121	121
R^2	0.820	0.761	0.555	0.667	0.396
Without subway line 15					
Treat	-0.3060**	0.3681***	-0.3674	-0.6190	-0.3239
	(-3.49)	(5.53)	(-0.86)	(-1.51)	(-0.80)
N	484	484	484	484	484
R^2	0.713	0.805	0.726	0.707	0.698
Without subway line 14					
Treat	-0.3288**	0.3862***	-0.4187	-0.7013	-0.3469
	(-3.29)	(4.81)	(-0.97)	(-1.53)	(-0.87)
N	484	484	484	484	484
R^2	0.717	0.728	0.739	0.713	0.724
Without both subway lines 15 *and* 14					
Treat	-0.5856***	0.2074**	-0.2918	-0.3588	-0.2281
	(-9.97)	(3.32)	(-1.25)	(-1.13)	(-0.95)
N	363	363	363	363	363
R^2	0.764	0.774	0.684	0.682	0.619

Notes: All regressions based on model specification (4); *Std. Err.* adjusted for 7 clusters for the seven days of the week; *t* statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9. Robustness Check: Choose Cutoff Point Arbitrarily Based on Baseline Model

	BPV	SPV	TCI(DA)	TCI(MP)	TCI(EP)
*Cutoff*1 Five days before					
	-0.2765	-0.0742	-0.0320	0.2549	-0.7946**
	(-1.02)	(-0.37)	(-0.09)	(0.64)	(-1.99)
Cutoff 2 Five days after					
	0.2361	-0.0577	0.0984	0.1251	-0.5477
	(0.94)	(-0.28)	(0.21)	(0.33)	(-1.39)
*Cutoff*3 Ten days before					
	-0.0865	-0.0122	-0.2272	-0.8568***	0.1778
	(-0.39)	(-0.07)	(-0.77)	(-2.66)	(0.47)
*Cutoff*4 Ten days after					
	0.4484	0.1667	0.1578	0.6219	0.2266
	(1.68)	(0.76)	(0.40)	(1.62)	(0.55)

Notes: N=605; regression based on model specification (4); *Std. Err.* adjusted for 7 clusters for the seven days of the week; *t* statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10. Robustness Check: Road Speed along Subway Line 7

Subway Line 7 (Dec.28 2014)				
City level variables	BPV	SPV	TCI(MP)	TCI(EP)
Treat	-0.4729**	0.1401	-0.0104	0.0944
	(-2.77)	(0.35)	(-0.04)	(0.26)
R^2	0.848	0.663	0.717	0.663
Speed around Line 7	WtE(MP)	WtE(EP)	EtW(MP)	EtW(MP)
Treat	0.7461	0.0467	0.6441	-0.2083
	(1.39)	(0.07)	(1.56)	(-0.25)
R^2	0.665	0.642	0.594	0.640

Notes: *N=212*, Obs. from 2014-09-01 to 2015-03-31; *t* statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. WtE and EtW indicate west-east and east-west direction, and MP and EP indicate morning peak (7:00-9:00am) and evening peak (17:00-19:00).

Figure 1. Map of Sample Subway Lines in Beijing

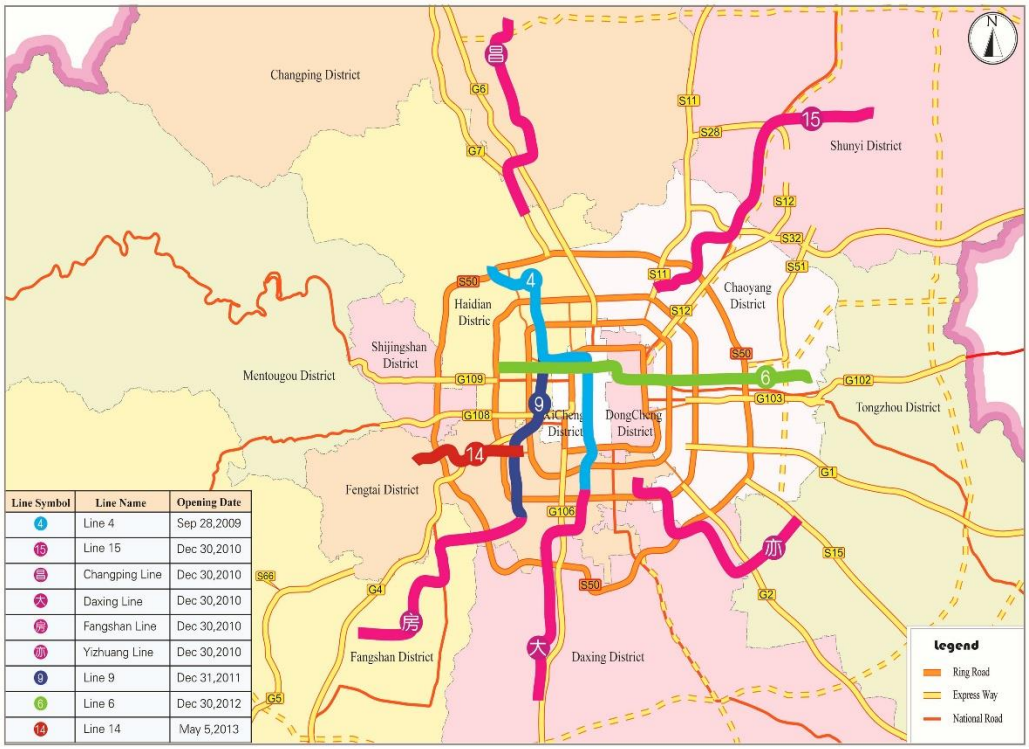
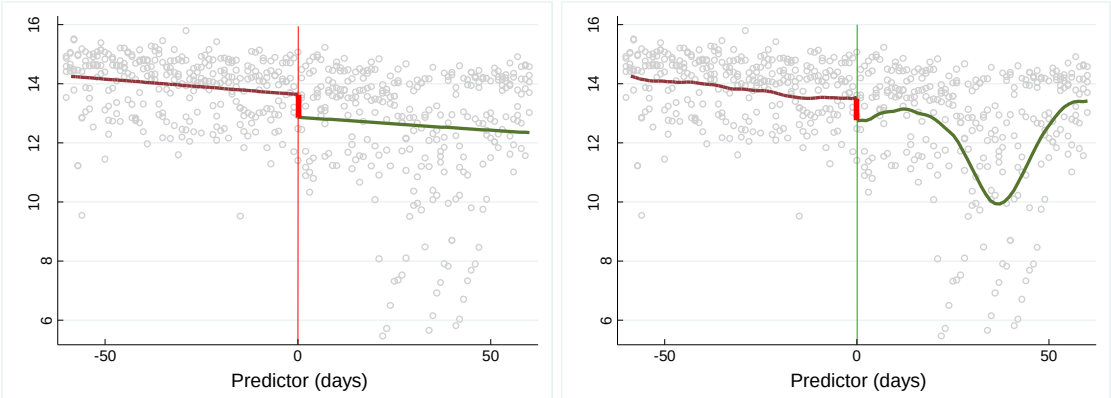
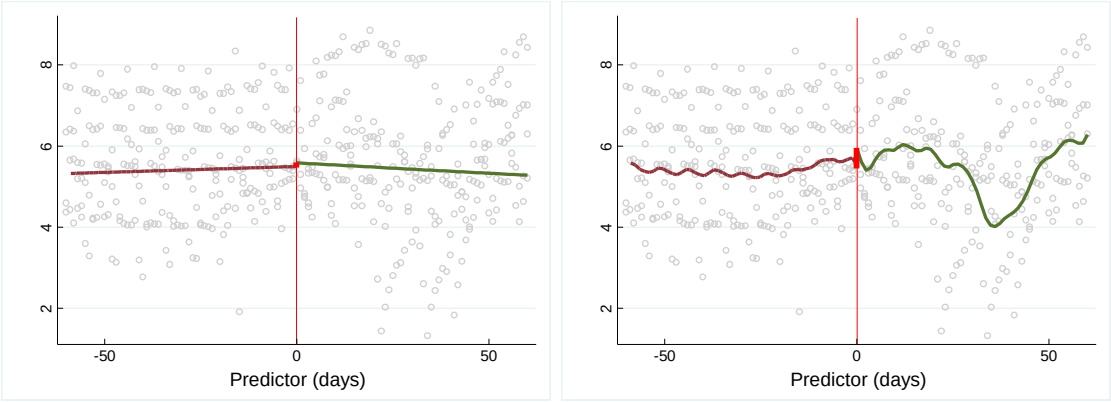


Figure 2. Local Linear vs. Polynomial in Bus Ridership RD.



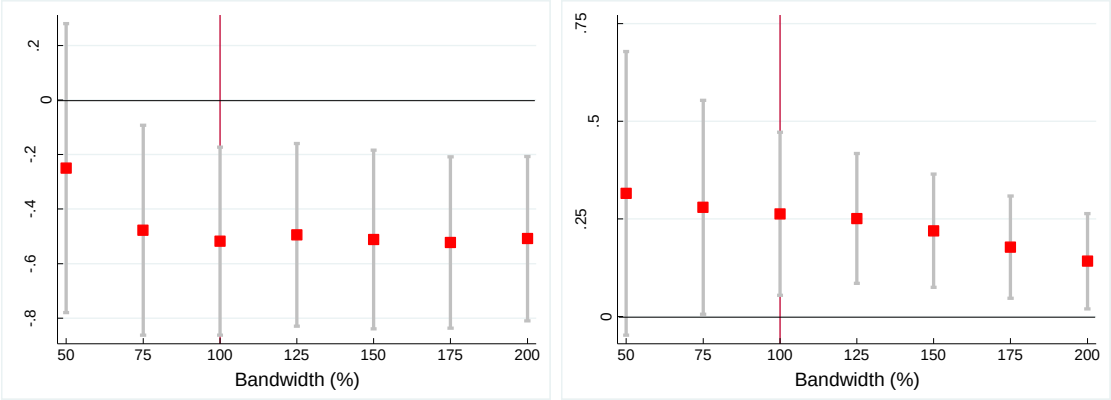
Notes: The estimated change in BPV just after the subway opening is -0.4524 (million) and is statistically significant (95% CI: -0.6321, -0.2727).

Figure 3. Local Linear vs. Polynomial in Subway Ridership RD



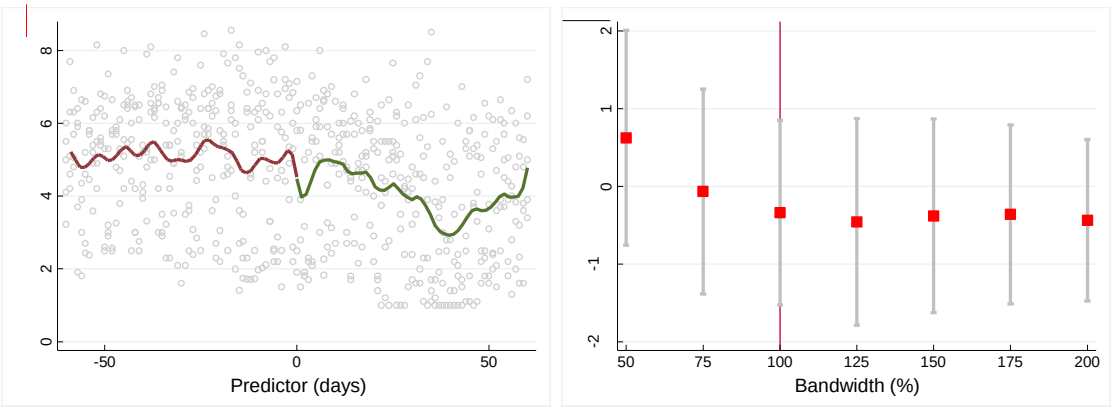
Notes: The estimated change in SPV just after the subway opening is 0.2463 (million) and is statistically significant (95% CI: 0.1034, 0.3893).

Figure 4. Change Bandwidth for Local Polynomial Smoothing in Bus and Subway Ridership



Notes: Gray bars indicate 95% CI at corresponding bandwidth.

Figure 5. Polynomial and Bandwidth in TCI (DA).



Notes: The estimated change in TCI (DA) just after the subway opening is -0.3219 (index) and is statistically insignificant with any bandwidth (95% CI:-1.1141, 0.4704).

Figure 6. Polynomial and Bandwidth in TCI (MP) and TCI (EP), Respectively

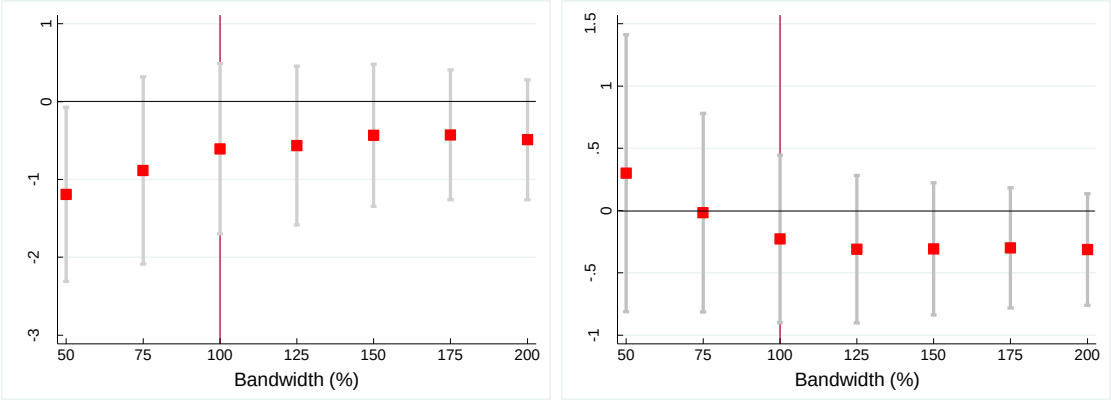
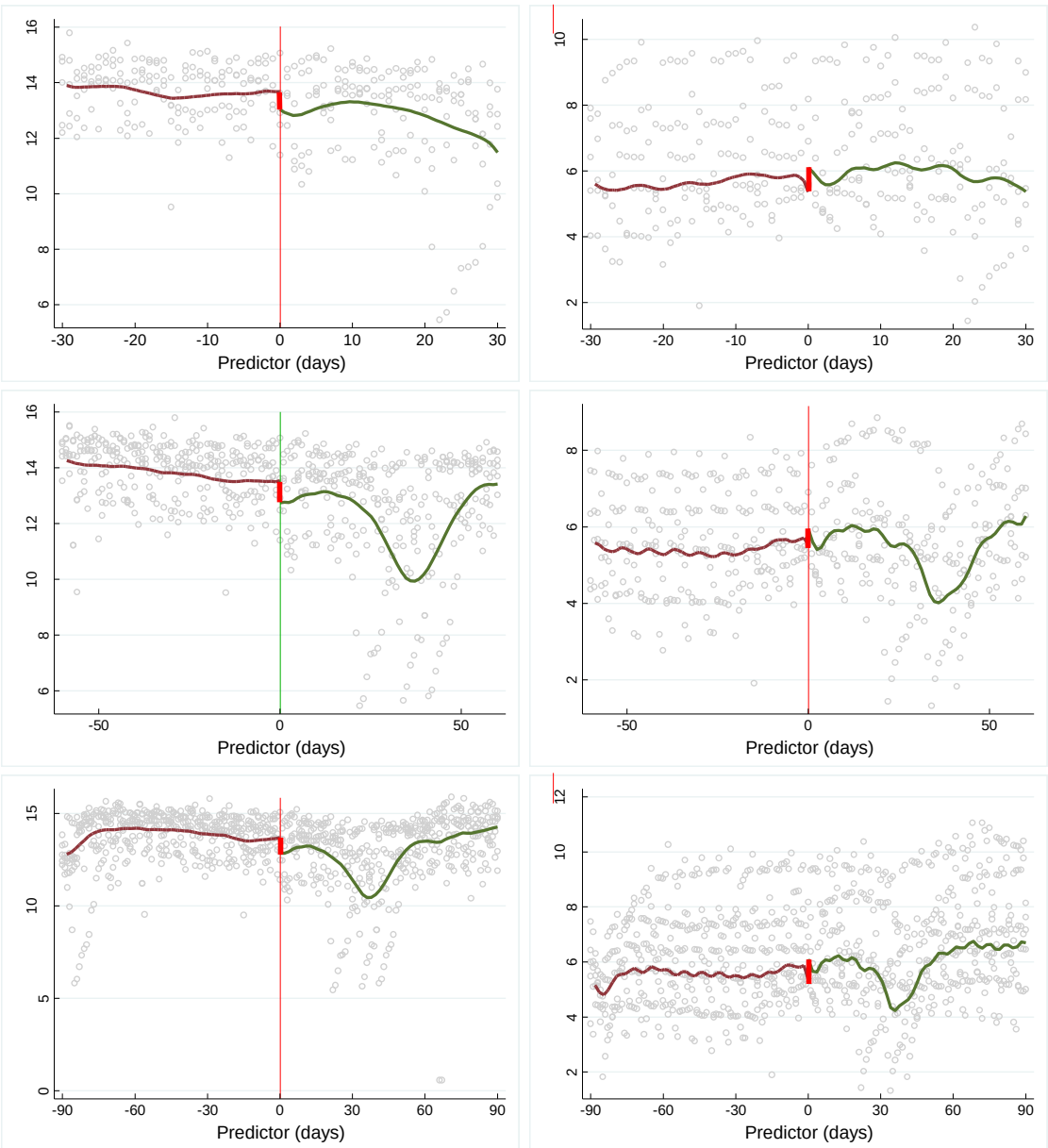



Figure 7. Robustness Check in Bus and Subway Ridership by Alternative Sample Selections: Change Sample Period from [-60, 60] to [-30, 30] and [-90, 90]. ([-60, 60] is our Baseline)