The Effect of Subway Expansions on Vehicle Congestion: Evidence from Beijing

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Abstract

Does public transportation reduce vehicle congestion? Using a regression-discontinuity framework, we examine the effect of six subway openings on short-run congestion in Beijing between 2009 and 2015. We find that vehicle congestion drops sharply immediately after new subway openings. In our central specification, each of the subway openings decreased delay times by an average of 15% in the short run over the city of Beijing.

1. Introduction

Road congestion is a significant problem in cities around the globe. The Centre for Economics and Business Research (2014) estimates the costs of congestion in the U.S., U.K., France, and Germany at $200 billion in 2013, about 0.8% of GDP in these countries.[6] Congestion is the largest negative externality from cars (Parry and Small 2005). It is particularly salient in developing countries like China, which suffers from notoriously choked motorways and severely polluted skies. According to the TomTom traffic index,[7] based on GPS device measurements, nine of the ten most congested cities are in the developing world.

One proposed solution to the issue of congestion is investments in public transportation. Public transportation like railways or buses can provide an attractive alternative to driving, freeing up roads. Since the relative value of public transportation increases as congestion goes up, public transportation can serve as an effective outlet to reduce the demand for roadways.

Economic theory is unclear on how investments in public transportation should affect congestion. In principle, each additional bus or subway rider is one less rider in a car, creating reductions in congestion. However, the law of peak-hour traffic congestion (Downs 1962) states that peak-hour traffic congestion will rise to match the maximum capacity of roads. This implies that investments in public transportation

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[6] Direct costs like the value of fuel and time wasted account for most of this total. Indirect costs, like the increased cost to goods and services from more costly transportation, account for about 60% of direct costs. These estimates are low, because they do not take into account environmental costs like air pollution or climate change.

[7] Available at https://www.tomtom.com/en_gb/trafficindex/. Website accessed May 9, 2016.

will have no impact on congestion, because cars taken off the road by public transportation ridership will eventually be replaced by drivers attracted to loosened roadways.

Empirical analysis of the effect of public transportation on congestion has been mixed.[8] Winston and Langer (2006) examine the correlation between congestion costs and lengths of bus line and subway line in a panel of U.S. metropolitan areas. They find that cities with longer lengths of commuter rail are also those with lower congestion costs, but that bus provision is correlated with higher congestion costs.

Duranton and Turner (2011), using a history-based instrumental variables strategy, find strong support for the law of peak-hour congestion. Consistent with this law, they calculate an elasticity of vehicle kilometers traveled (VKT) with respect to roads provided of nearly 1. Additionally, they find that increased provision of buses has a small and statistically insignificant impact on VKT, suggesting that public transit will have no effect on congestion.

Each of the previous results were established using cross-city data, and examine the law of peak-hour congestion over the long run. However, there is growing evidence that public transportation does affect congestion in the short-run. Anderson (2014) and Adler and van Ommeren (2016) use the setting of transit strikes to examine the impact of sudden public transit closures on road congestion. Each paper finds that peak-hour congestion sharply increases during transit strikes, suggesting that sudden drops in the availability of public transportation generate significant costs through intensified congestion.

Our current work provides evidence adding to the body of empirical literature examining the effects of public transportation on vehicle congestion. Our primary question is to examine how subway openings in Beijing impact demand for other forms of transportation in the short run, measured by bus ridership and vehicle congestion. Congestion is a serious issue in Beijing. In 2009, prior to the opening of the subway lines in our study, a trip in Beijing took 71% longer on average in actual travel conditions than it would have in uncongested conditions.

In principle, one might calculate the effect of public transportation on congestion by regressing congestion measures directly on subway ridership. However, this approach is likely to be flawed because of other confounding factors driving both variables. For example, both congestion and subway ridership are likely to be high during rush hour, or during seasons of high travel.

Our regression-discontinuity strategy resolves these problems by leveraging the sharp discontinuities in subway traffic generated by new subway openings. After the Olympics in 2008, Beijing engaged in an unprecedented expansion of its subway system. We examine how six separate subway openings[9] affect daily demand for other forms of transportation between the period of 2009 and 2015.

To be specific, we regress daily transportation demand on a dummy variable for new subway openings in a regression discontinuity framework where time is the running variable. Our key identifying assumption is that all other factors influencing the demand for travel are smooth in the vicinity of

[8] Beaudoin et al. (2015) survey this literature, finding that there is "no clear consensus" in the literature regarding the effect of public transportation supply on vehicle congestion.

[9] In total, twelve new subway lines were opened. However, some of these lines coincided on the same date; as a result, we observe only six opening dates (see table 1 for details.) Throughout the paper, we use the term "subway opening" to describe one of the six opening dates, and the term "new subway lines" to describe one of the twelve lines that were opened.

subway opening dates except the new subway lines themselves. Changes to other contributors to travel demand, such as the population and economy of Beijing, do not threaten our identifying assumption as long as they evolve smoothly in the vicinity of the discontinuity. As a result, discontinuous changes in our outcomes of interest at the time of the subway openings can be attributed to the sudden change in the availability of public transportation.

We find that subway openings cause large drops in congestion. In our primary specification, each of the subway openings decreased delay times by an average of 15% over the city of Beijing. Similarly, morning rush hour delay times declined 24% on average. We also observe decreases in evening rush hour congestion, but these are not statistically significant. Finally, we examine the measured road speed on a set of 22 roads. Road speeds generally increase for morning rush hour traffic, and road speeds for roads close to the newly opened subway increase during evening rush hour traffic.

We test whether our findings are robust to alternative explanations. Because four of the six openings fall very near the end of the calendar year, coinciding holidays are a potential concern, but we confirm that our results are not being driven by changes in traffic related to these holidays. Two of our subway openings occur around the implementation dates of other major transportation policies, and our results are robust to the exclusion of these openings. Our results are also robust to a large number of subsamples and different specifications.

Because two openings occurred four months apart from each other, our primary estimates use only a 60-day period before and after each subway line opening. By dropping these two openings, we can improve our precision by extending our sample period to 180 days before and after subway line openings. We find that large congestion reductions of almost the same magnitude as our initial findings are observed.

Since our empirical strategy relies on discontinuities in transportation patterns occurring at the dates of subway openings, our findings apply only to the period immediately following each subway opening. We are unable to discern the long run impact of subway openings, and the law of peak-hour traffic congestion may still apply in longer time horizons. Further, our strategy prevents us from measuring the cumulative impact of all openings, which would also require long-run estimates.

Our results provide three contributions to the literature connecting public transportation and congestion. First, we are the first paper to tie new subway openings and congestion.[10] Our data allow us to study six distinct openings. Second, rather than study short-term stoppages in public transportation, we study subway openings. This focus is potentially more policy-relevant for government officials, who can invest in new subway lines but would not induce short-term shutdowns in public transportation. Moreover, behavioral responses to new subway openings may be different than responses to temporary stoppages of bus and railway systems. Third, we provide evidence in China, one of the world's most important settings for studying transportation policy because of its size and impact on global environmental issues. Public transportation demand and congestion are particularly important issues in Beijing, which struggles under the dual burdens of dense traffic and heavy air pollution.

[10] Chen and Whalley (2012) also use a subway opening in a regression-discontinuity design. Their outcome variable of interest is air quality in Taipei.

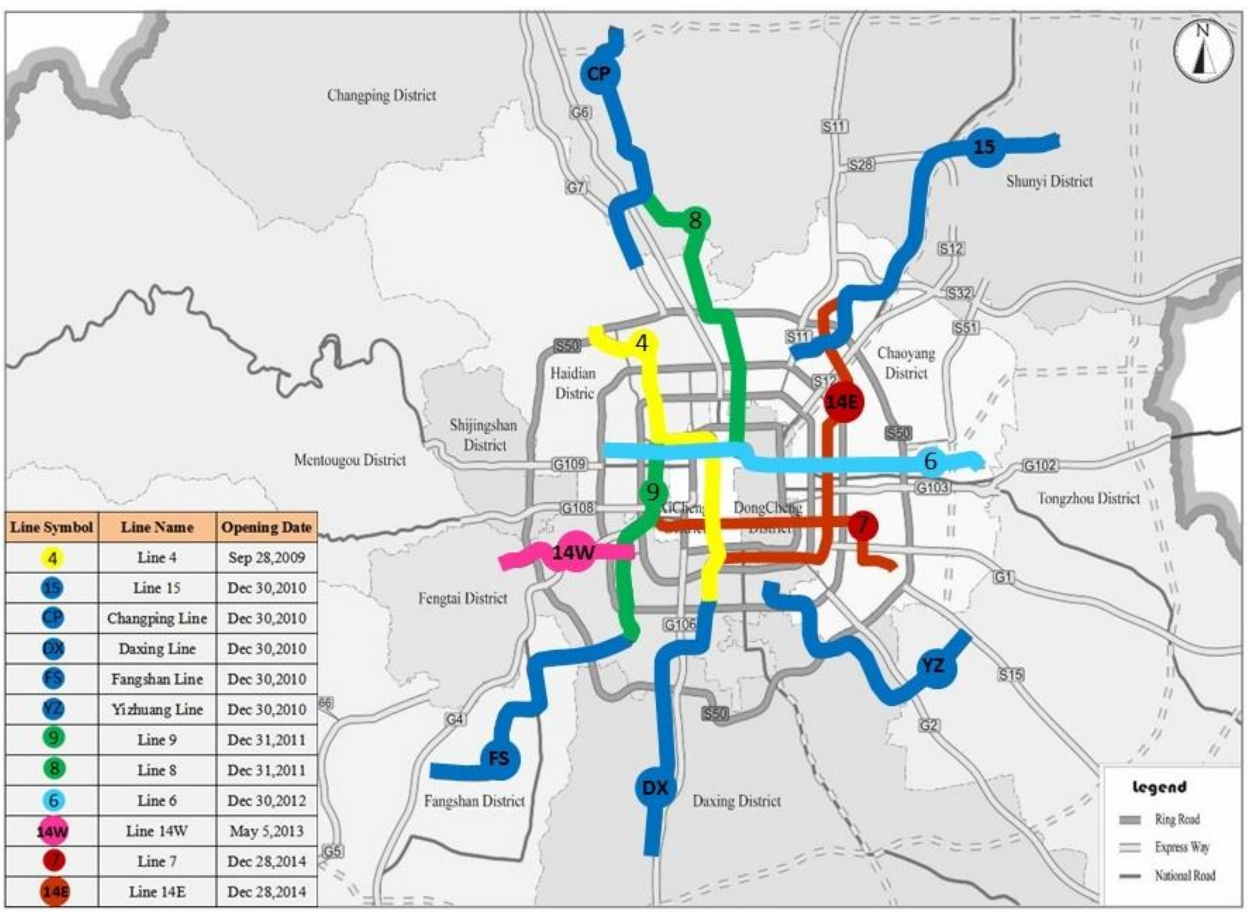
The remainder of the paper is organized as follows. Section 2 provides an overview of Beijing's subway development. Section 3 explains using a simple theoretical model how travelers might respond to new subway lines. Section 4 lays out the empirical framework and data. Section 5 presents our findings and discusses robustness checks for these results. Section 6 concludes.

2. Background

Beijing’s rapid development has created a host of transportation problems. Its population grew almost 50% between 2000 and 2010, from 13.6 million to 19.6 million. Its demand for cars grew even faster, with the number of vehicles increasing by 250% in that decade (Yang et al. 2014). This growth has inflicted a heavy cost: Beijing’s air pollution is notorious and it suffers from intense vehicle congestion. In response, Beijing has prioritized the development of public transportation to ease its significant environmental problems and relieve the burdens on its roads.

Spurred in part by the 2008 Olympic Games, Beijing engaged in an unprecedented expansion of its subway system. It invested about US$20 billion on subways alone between 2009 and 2014, averaging one opening per year during this interval.

Figure 1. Map of Sample Subway Lines in Beijing



This study covers these six subway openings. Twelve new subway lines opened on these dates, totaling 210 kilometers in length. These openings doubled the mileage of Beijing’s subway system. As shown in figure 1, the new subway lines are geographically dispersed. Some routes cross the middle districts of the city while others extend Beijing's subway network into its outer suburbs.

We summarize these openings in table 1. They vary substantially in size and length, with the opening of lines 15, CP, DX, FS, and YZ creating the longest new stretches of subway and creating the largest expansion in the network of stations. Each line varies significantly in the number of passengers, with line 4 the largest at a half million passengers per day.

Although the process of opening a subway line in China is tightly managed, opening dates for subway lines cannot be perfectly controlled. City officials wishing to expand the subway network of their city must first apply to a federal agency, the National Development and Reform Commission (NDRC). Applications are typically submitted six to eight years before the subway line is scheduled to open.

Once an application is approved, the NDRC publishes notification of its approval on its official website. As a result, each subway opening is public information. A city government receiving permission will add the construction of the new line to its local development plan. Because these development plans are essential elements in evaluations of government officials, local governments dedicate themselves to opening subway lines on schedule.

Table 1. Sample Subway Lines and Selection of Sample Period

Subway Opening	Subway Lines	Opening Date	Sample Period	Stations	Length (km)	Cost (billions of RMB)	Avg. Daily Ridership (millions)
1	Line 4	9/28/2009	7/30/09 – 11/27/09	24	28.2	15.8	0.527
2	Lines 15, CP, DX, FS, YZ	12/30/2010	10/31/10 – 2/28/11	54	122.4	47.2	0.155
3	Lines 8, 9	12/31/2011	11/1/11 – 2/29/12	13	16.5	19.3	0.105
4	Line 6	12/30/2012	10/31/12 – 2/28/13	20	30.4	28.0	0.340
5	Line 14W	5/5/2013	3/6/13 – 7/4/13	7	12.4	3.6	0.041
6	Lines 7, 14E	12/28/2014	10/29/14 – 2/26/15	19	23.7	29.4	0.263

Notes: The sample period of the main specification is 60 days before and after the date of the opening.

There is some uncertainty in the exact date a subway will open. Deadlines on applications to the NDRC and in local development plans are always set to a year, not to a day. The most important condition for opening a new line is that the new subway line is qualified to be put into operation; in other words, it must pass safety inspections and operate as intended. Exact opening dates cannot be planned because of the inevitable idiosyncrasies of construction in a large city. Some subway line construction projects run smoothly; they finish with months to spare before the end of the year. More often, large construction projects are subject to unexpected obstacles, and open at the end of December as public officials race to meet their development plan goals. Table 1 illustrates this dynamic. Four of the six subway openings occurred at the end of December.

In addition, our interviews with Beijing government officials suggest that the exact subway opening date is set so that the mayor or municipal party secretary of the city government can attend the opening ceremony. This is necessary because subway construction is a highly visible development measure undertaken by city governments. A special government working team is set up led by either the mayor or the municipal party secretary. Because the mayor or municipal party secretary typically has a very busy schedule, the exact opening date must be coordinated to occur when this person has time to attend the official opening ceremony. Both the idiosyncrasies of construction and the necessity of including the attendance of this official make it clear that subway opening dates are not selected in relation to the travel outcomes we study in this paper.

3. Empirical Framework

We first describe briefly how a new subway line is likely to affect congestion. Consider a representative traveler deciding whether to take a subway line. This traveler's decision is likely to depend on several factors such as the total travel time, the time spent walking and the monetary cost of the trip. These will differ depending on whether the traveler takes the subway, or whether she takes an alternative form of transportation such as a bus or taxi.

Now consider the opening of a new subway line.[11] Because the passenger can always ride the same lines as she did before the subway opening, a new subway line will expand the set of options for the passenger and will either leave the traveler indifferent or better off. As a result, the representative traveler is unambiguously more likely to ride the subway and less likely to take other forms of transportation.

However, this result is conditional on the traveler taking a given trip, and the total number of trips may change in general equilibrium if the costs of travel decrease with the new subway opening. This is an empirical matter to investigate.

3.1 Regression Discontinuity Approach

In principle, one might estimate the effect of increased subway traffic on congestion by performing Ordinary Least Squares regressions with congestion as the dependent variable and subway ridership as the independent variable. However, this approach is likely to be biased because there are often observable and unobservable characteristics correlated with both subway ridership and congestion, such as travel demand. For example, large government meetings in Beijing bring in significant numbers of additional commuters, leading to both high subway ridership and high vehicle congestion.

To address these endogeneity concerns, we estimate as our primary specification a discontinuity based ordinary least squares model. In order to identify the effect of subway ridership on travel outcomes, our empirical strategy leverages the sharp discontinuities in subway ridership when new lines open.

Specifically, we utilize the following sharp regression discontinuity design:

$$Y_t = \beta_0 + \beta_1 SubwayOpen_t + \beta_2 X_t + \beta_3 SubwayOpen_t X_t + \beta_4 f(X_t) + \beta_5 Z_t + e_t \quad (1)$$

In equation (1), our outcomes of interest Y_t are indicators of travel demand on day t. Congestion is the most important, while bus ridership and subway ridership are also interesting. The variable $SubwayOpen_t$ is a dummy indicating whether the new subway lines are open on t. The variable X_t is a

[11] In the setting of Beijing, subway fares remained constant until 2014, with no additional charge even if the passenger rode the subway continuously and transferred lines multiple times.

running variable representing the time trend: the difference in the number of days between the subway opening and day t. Before the subway opening, X_t is negative; after the opening, X_t is positive. The function $f(X_t)$ is a k-th order polynomial function, used to flexibly control for time-series variation in transportation demand that would have occurred in the absence of the subway openings.

We also include Z_t, a vector of other control variables that may affect transportation. In our regressions involving Z_t, we include four types of additional controls: dummies for the day of week, dummies for extreme weather incidence, dummies for which license plates are excluded from Beijing roads that day, and dummies for which subway opening is being considered. We reason that the first three control variables can impact patterns of transportation. The fourth dummy variable controls for any fixed factor affecting Y_t which differ between openings, such as the larger population and larger economy levels of Beijing in later years.

The variable of interest is β_1, the local average treatment effect of the subway opening on other forms of transportation use. The size and direction of this effect could vary, depending on how city residents respond to new subway lines. If new subway lines attract passengers from other modes, subway openings will negatively impact bus traffic and ease congestion. However, if new public transportation routes attract new passengers to travel rather than stay home, subway openings could have no effect on measures of travel demand.

The key assumption behind this identification strategy is that the only factor affecting travel demand in the vicinity of subway opening dates is the subway opening. Both observable and unobservable factors affect transportation smoothly in the neighborhood of the subway opening date. Our higher order polynomial function allows us to control for changes from all other factors so long as they are continuous. Other work using a similar methodology in different settings includes Chen and Whalley (2012) and Davis (2008).

We implement this approach using daily observations 60 days before and 60 days after subway openings. We use the period including 60 days before and after the opening of the subway to ensure no overlap between the sample periods of each subway opening. Line 6 opened December 30, 2012, and line 14 opened May 5, 2013.

3.2 Threats to Identification

Our identifying assumption is that demand for transportation would have changed continuously in the absence of subway line openings. This assumption is reasonable so long as there are no large shifts in the drivers of transportation demand timed with the openings of subway lines. Gradual shifts in transportation demand, which do not threaten our identification, happen on a continual basis: Beijing's economy is growing rapidly, its population is increasing, and the fleet of vehicles in the city continues to enlarge. The flexible polynomial included in our regressions accounts for these continuous changes.

Only discontinuous shifts timed with the six subway openings pose a threat to our identification strategy. A discontinuous shift could occur if subway openings are simultaneous with events that produces changes in travel demand. For example, if Beijing government officials strategically opened Beijing subway lines to coincide with events that decreased transportation demand, our estimates of β_1 would be overstated. However, as explained in Section 2, many details about this setting suggest that precisely timing subway opening dates is not possible.

A second concern in our sample is the extent to which Chinese national holidays can interfere with our results. Several subway line openings occur just before the major holidays of the calendar new year and the lunar new year. We handle this concern by dropping all national holidays in our main specifications. In our robustness checks, we also drop days around holidays to account for the possibility that low transportation demand is observed because some people leave early for vacation or return late from it.

A third concern is the presence of alternative policies that came into effect during our sample period. The most prominent of these policy changes was the January 2011 implementation of the Beijing vehicle license plate lottery system, which sharply reduced the number of new cars on Beijing's roads. A second potentially important policy change was a revision in Beijing's taxi fares in June 2013. We address this concern by dropping the subways openings near these events.

A fourth concern might be that construction activity associated with opening new subways creates congestion. For example, to build street level subway entrances, streets and sidewalks must be closed, possibly increasing congestion; this congestion is alleviated when the new subway line opens. However, this possibility does not fit with the safety regulations of Chinese subways. According to the national standards of subway construction in China, all fully constructed subway lines must be tested for safety for three months before opening to local residents. Since our primary sample period includes congestion levels within only two months of opening, it would not include any street closures or construction activities.

3.3 Description of Data

Our empirical analysis leverages daily data on subway ridership, bus ridership, and traffic congestion. These administrative data were obtained from Beijing Daily Transport Operation Monitoring, released by the Transport Operation Control Center of Beijing. These data are summarized in table 2. Total bus traffic is roughly double that of subway traffic, reflecting the large network of buses available in Beijing. There are nearly 23,000 buses in Beijing covering 170,000 routes per day.

We break out subway traffic from new and existing lines in table 2. Traffic from new lines is zero before the opening of new subway lines, and jumps to an average of 239,000 passengers per day after the openings. Subway traffic appears slightly smaller after subway line openings in the top panel, but when we exclude holidays and weekends from the data in the bottom panel, subway traffic from existing lines is basically flat.

Table 2 also reports simple averages for bus ridership and motorway congestion. After new subway lines are opened, both the passenger volume of buses and the traffic congestion index (TCI) decrease by large and statistically significant amounts after subways are opened.[12] These simple means are supportive of the finding that new subway lines lower usage of other forms of transportation, but does not account for pre-existing trends or other factors that may affect congestion patterns. As a result, we utilize the regression discontinuity in equation (1) to separate out the effect of new subway openings from other factors affecting traffic demand.

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[12] An astute reader of table 2 may notice that bus passenger volume drops by 1.1 million passengers while subway passenger volume rises by only 0.25 million passengers. We offer possible explanations for this apparent discrepancy in Appendix A.

To measure congestion, we use TCI, the official standard by which congestion is measured in China. The Beijing Municipal Commission of Transport (BMCT) collects readings on Beijing's road speeds through a large fleet of taxis using satellite navigation and wireless technology at 15-minute intervals. The BMCT assigns weights to different roads and calculates the TCI as a weighted average across Beijing.

Table 3 illustrates the relationship between the TCI and the time needed for travel. If all of Beijing's roads flow in an unrestricted manner, the TCI is 0, while if all of Beijing's roads are severely congested, the TCI is 10. For TCI values between 2 and 8, a one-unit increase in TCI corresponds to an approximately 15% increase in travel time. We have three measures of TCI available: total average TCI, morning peak traffic, and evening peak traffic. Our data consist of daily measurements of each of these over the period January 2009 to May 2015.

The regression discontinuity approach removes the sources of endogeneity described in the OLS approach so long as those variables change smoothly in the vicinity of the subway opening date. Figure 2 provides supportive evidence for this assumption, plotting daily average ridership of the Beijing subway system for existing lines alongside rider for the newly opened lines. Ridership of existing lines changes smoothly in the vicinity of subway openings, suggesting that factors contributing to demand for transportation are also continuous.[13] New subway lines, plotted on the right axis, jump at the subway openings from a ridership of zero for an unopened line to a large and sustained number of passengers.

Alongside official holidays, other special circumstances such as extreme weather may affect transportation choices. We account for five types of extreme weather: heat wave, cold spell, rainstorm, gale and snow. These variables are summarized in table 2.

A few other details of our empirical strategy are worth discussing here. First, we cluster our standard errors according to Beijing's unique patterns of transportation.[14] Daily travel volume differs dramatically by day of the week, with Fridays the most popular days to travel and weekends the least popular. In addition, Beijing employs a rotating system of license plate bans, with two trailing digits banned each weekday. For example, license plates with trailing digits "1" and "6" are banned on the same day, but they might be banned on a Monday in one month and a Tuesday in the next month. This is particularly salient because the quantity of each license plate number is not random, but varies according to Chinese perceptions of lucky and unlucky numbers.[15] Because of these unique features, we cluster our standard errors using the interaction of weekday and which license plate pair is banned on that day.

[13] There is an apparent drop in subway ridership from new lines four days after the openings in figure 2. This drop occurs because figure 2 omits holidays. On the day four days after subway openings 1, 2, 3, and 4, there was a holiday. As a result, this point on the figure includes only subway openings 5 and 6. These openings had relatively small passenger volume and occurred late in our sample date period. As a result, ridership on opening lines looks artificially small and ridership on already opened lines looks artificially large on this day.

[14] We examine other forms of standard error in Appendix D, and find that our results are unaffected by this choice.

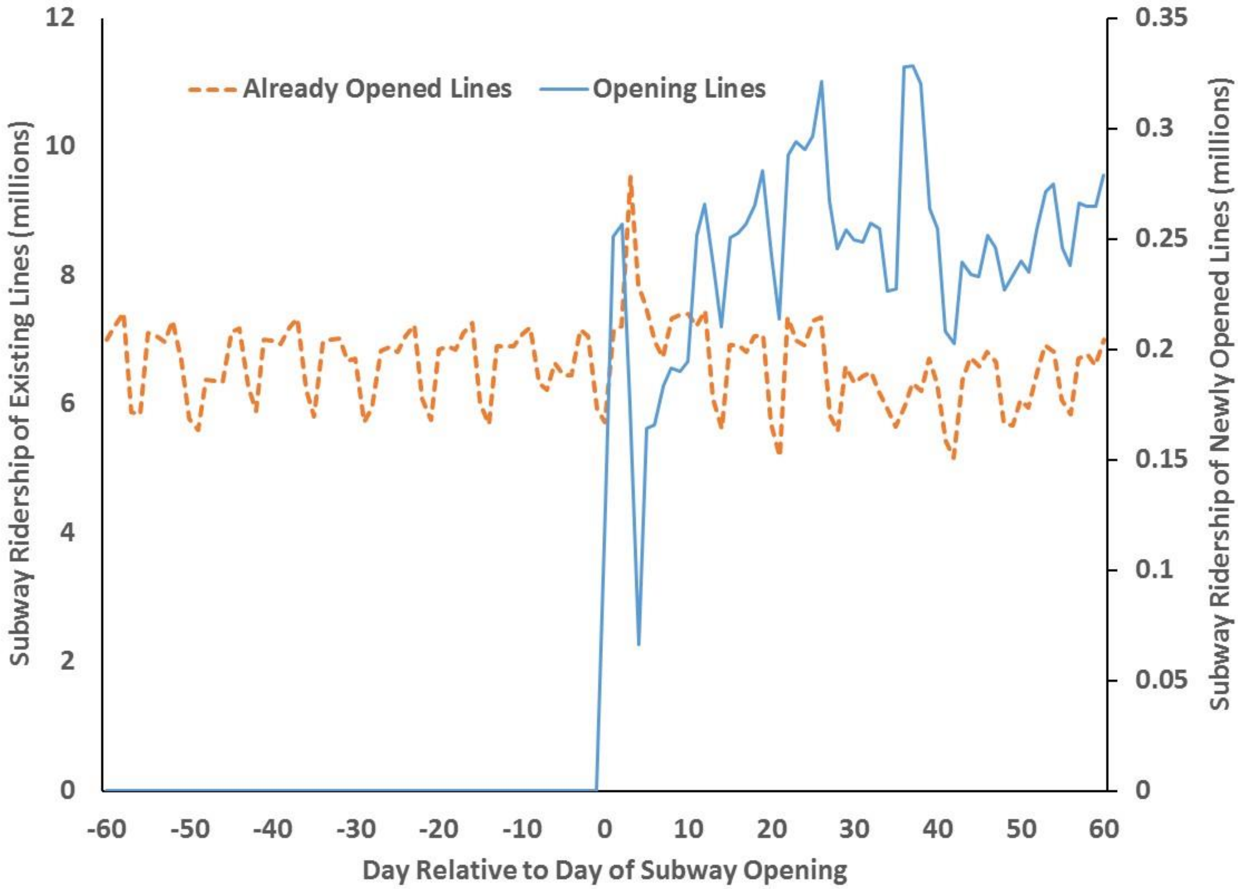
[15] Because car bans can also contribute to congestion patterns, we verify in table 2 that the percentage of cars banned on each day is symmetric before and after subway openings.

Table 2. Summary Statistics

Variable	Full Sample	Before Openings	After Openings	Difference
Includes Holidays and Weekends (N = 726)				
Newly Opened Subway lines (millions of riders)	0.120	0	0.239	0.239***
	[0.006]	[0]	[0.009]	[0.009]
Existing Subway Lines (millions of riders)	6.430	6.727	6.138	-0.589***
	[0.079]	[0.109]	[0.112]	[0.156]
Bus Passenger Volume (millions of riders)	13.032	13.829	12.248	-1.581***
	[0.071]	[0.056]	[0.115]	[0.129]
Traffic Congestion Index (TCI, Daily Average)	4.593	5.156	4.040	-1.116***
	[0.070]	[0.090]	[0.099]	[0.134]
Traffic Congestion Index (TCI, Morning Peak)	3.629	4.089	3.177	-0.912***
	[0.084]	[0.109]	[0.103]	[0.150]
Traffic Congestion Index (TCI, Evening Peak)	5.518	6.195	4.853	-1.342***
	[0.081]	[0.999]	[0.117]	[0.154]
Holiday (0,1)	0.101	0.039	0.161	0.122***
	[0.012]	[0.011]	[0.021]	[0.024]
Extreme Weather (0,1)	0.044	0.044	0.044	-0.001
	[0.008]	[0.019]	[0.011]	[0.015]
Percentage of cars not banned (0, 100)	80.0	80.0	79.9	-0.100
	[0.150]	[0.207]	[0.207]	[0.300]
Excludes Holidays and Weekends (N = 475)				
Newly Opened Subway lines (millions of riders)	0.117	0	0.254	0.254***
	[0.008]	[0]	[0.011]	[0.011]
Existing Subway Lines (millions of riders)	6.663	7.138	6.963	-0.176
	[0.092]	[0.129]	[0.130]	[0.184]
Bus Passenger Volume (millions of riders)	13.403	14.373	13.248	-1.125***
	[0.064]	[0.039]	[0.093]	[0.098]
Traffic Congestion Index (TCI, Daily Average)	4.978	6.001	5.002	-0.999***
	[0.079]	[0.070]	[0.096]	[0.117]
Traffic Congestion Index (TCI, Morning Peak)	4.202	5.223	4.221	-1.003***
	[0.099]	[0.077]	[0.105]	[0.129]
Traffic Congestion Index (TCI, Evening Peak)	5.699	6.789	5.759	-1.031***
	[0.087]	[0.099]	[0.124]	[0.157]
Extreme Weather (0,1)	0.048	0.053	0.044	-0.009
	[0.010]	[0.014]	[0.014]	[0.020]
Percentage of cars not banned (0, 100)	80.0	80.0	79.9	-0.100
	[0.150]	[0.207]	[0.207]	[0.300]

Notes: These summary statistics report average transportation usage levels 60 days before and after the 6 subway stations openings. Other variables in our research include dummies for weekdays and subway lines, respectively. For brevity, they are not reported here. Extreme weather includes *heat waves, cold spells, rainstorms, and gale and snow*, based on meteorological definitions at Baidu Encyclopedia (http://baike.baidu.com/).

Figure 2. Ridership on the Beijing subway system near subway openings



Notes: This chart represents the average of the 6 subway line openings we explore in this paper. We exclude holidays in this graph. The X-axis represents the number of days from the opening of the new lines. All passenger traffic numbers are in millions.

Table 3. Traffic Congestion Index (TCI) Definitions

TCI	Description	Travel Time
0 - 2	Smooth	1 minute
2 - 4	Basically smooth	1.3 – 1.5 minutes
4 - 6	Slightly congested	1.5 – 1.8 minutes
6 - 8	Moderately congested	1.8 – 2.0 minutes
8 - 10	Seriously congested	>2.1 minutes

Notes: Travel time corresponds to the amount of time to travel a given distance. This time varies, depending on the speed of the measured road in uncongested circumstances.

Second, our baseline model uses a third-order polynomial, which gives more weight to samples near the cutoff than higher-order polynomials (Gelman and Imbens 2017). This functional form allows nonlinearity in transportation behavior, as long as these trends are continuous. First-order and second-order polynomials do not seem appropriate because the dependent variables appear non-linear, as shown in figure 3. Our primary results are qualitatively stable to the order chosen, which we show in our robustness checks.

Third, we include only weekdays and non-holidays in our estimation. Most residents of Beijing go to work or school on weekdays. Weekend and holiday travel is most likely to be driven by irregular factors that are not comparable between time periods, such as events in Beijing or vacation trips.

4. Empirical Results

4.1 Regression Discontinuity Results

We now estimate the average marginal effect of new subway openings on the patterns of transportation in Beijing using equation (1). We report our results in table 4. Each entry in this table represents the result of a separate regression, with the dependent variable in the column headings and the functional form of the regression in the row headings. The coefficient reported in each cell is β_1, the local average treatment effect of the subway opening.

In the first panel, we do not include covariates and take a simple average of the six subway openings for our results. In the second panel of this table, we include covariates that may influence travel patterns: dummies for the day of the week, for extreme weather, for which license plates are excluded from Beijing roads, and for the subway opening that is under consideration. The magnitude and statistical significance of the coefficients in this table are generally stable to the presence or absence of additional covariates. The results of these rows give us the unweighted average effect of one of the six subway openings in Beijing.

In the third and fourth panels of table 4, we weight observations by the average passenger volumes of the opening lines. Weighting observations by volume is intuitively sensible because we expect the effect of subway openings on transportation patterns to be larger if passenger volume on them is higher. The results of these rows give us the ridership average partial effect of subway openings in Beijing. Specification 4, with both subway line weighting and additional covariates, represents our preferred method of estimating the impact of subway openings on bus traffic and vehicle congestion.

The first two columns give the average effect of new subway openings on total subway traffic and on existing subway lines. The estimates suggest that these openings add sharply to total traffic, but do not diminish traffic for existing lines. Existing subway lines do not appear to change in ridership when new subway lines open. New subway openings also appear to draw away riders from buses, as demonstrated in column 3.

Our estimates of the impact of subway openings on congestion are in columns 4 through 6 of table 4. We find that subway line openings have a large and statistically significant impact on overall congestion levels in Beijing. Average daily congestion decreased by 0.728 after subway openings in our preferred specification of panel 4, a large and statistically significant decrease from the pre-opening level of 5.408.

Table 4. Regression Discontinuity-Based Results

Dependent Variable	Ln(All SPV)	Ln(Existing SPV)	Ln(BPV)	TCI (all)	TCI (morning)	TCI (evening)
Specification 1: Unweighted estimation						
Subway Open	0.046***	0.007	-0.033***	-0.687***	-0.750**	-0.631**
	[0.015]	[0.012]	[0.009]	[0.253]	[0.297]	[0.270]
R^2	0.794	0.879	0.456	0.296	0.221	0.261
Specification 2: Add covariates						
Subway Open	0.053***	0.001	-0.037***	-0.652***	-0.796**	-0.514**
	[0.011]	[0.014]	[0.010]	[0.221]	[0.298]	[0.188]
R^2	0.901	0.904	0.559	0.493	0.512	0.453
Specification 3: Weight by passenger volume						
Subway Open	0.099***	0.027	-0.024***	-0.851**	-1.139***	-0.571
	[0.015]	[0.015]	[0.010]	[0.319]	[0.358]	[0.345]
R^2	0.776	0.910	0.525	0.294	0.280	0.215
Specification 4: Weight by passenger volume and add covariates						
Subway Open	0.117***	0.028*	-0.023***	-0.728***	-1.120***	-0.343
	[0.013]	[0.016]	[0.009]	[0.302]	[0.362]	[0.295]
R^2	0.830	0.927	0.668	0.578	0.562	0.485
(N = 475) for all regressions						

Notes: This table reports results of regressions of equation (1) when the dependent variable is bus passenger volume (BPV), subway passenger volume (SPV), or the traffic congestion index (TCI). "All SPV" refers to total subway passenger volume, and "Existing SPV" refers to subway passenger volume less that added on the newly opened lines. The reported coefficient in each cell is the coefficient on "Subway Open," a dummy variable indicating whether the new subway line had opened. All regressions include a third-order polynomial in the predictor. Holidays and weekends are excluded from these models. Regressions with "covariates" contain weekday dummies, dummies for which license plates are excluded from Beijing roads that day, extreme weather dummies, and dummies for subway line. All standard errors are clustered using a dummy for the interaction of the weekday and which license plates are excluded that day.

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In order to translate these TCI levels into travel times, we utilize the translation summarized in table 3. The starting average TCI level of 5.408 implies that a route that takes one minute without congestion will instead take 1.71 minutes at this level of traffic. If TCI falls by 0.728, that same trip will take 1.60 minutes, a (0.71-0.60)/0.71 = 15% reduction in delays that applies across the entire city of Beijing.

The point estimate of 0.728 for the decrease in TCI caused by subways has a 95% confidence interval of between -0.080 and -1.375. This corresponds to a reduction in delays of between 2% and 29%.

Strictly speaking, this estimate applies only to the discontinuity, and applies only to weekdays and non-holidays. When we include weekends in our estimates, we find that the standard errors increase so that we cannot conclude statistical significance for the effect of subway openings.

A 15% reduction in congestion is large, and it is reasonable to ask whether those reductions are reasonable relative to the number of new passengers on subways. We compare our results to those of a second policy in Beijing: driving restrictions based on license plate numbers. We relegate this discussion to Appendix B, but the basic finding is that the 0.728 drop in TCI connected with 254,000 new subway passengers is not inconsistent with changes in congestion related to changes in the number of license plates bound by vehicle restrictions.

We also compare our findings to those of Anderson (2014), who uses subway strikes in Los Angeles to examine the effect of shutting down the metro system on congestion. The LA transit system serviced 200,000 passengers per weekday by rail, and 1.1 million by bus. The headline result of Anderson (2014) is that a wholescale shutdown of this system increased delays by 47%, a result about 3 times larger than the 15% we found. So although Los Angeles and Beijing are very different, our estimate and those of Anderson (2014) are not entirely inconsistent.

Columns 5 and 6 further illuminate the effect of subway openings on vehicle congestion. Column 5 provides our estimates for morning peak traffic congestion; we find that this index decreases by 1.120 in our preferred specification, a very large decrease from the 4.580 pre-opening level and corresponding to a 24% reduction in delay times. Although the point estimates for evening peak congestion suggest that subway openings decrease it, the result is not statistically significant in our main specification. Evening peak congestion is generally much higher than morning peak congestion, and it is possible that cars taken off the road during periods of very high congestion are quickly replaced when cars are removed by subway openings.

We next consider graphical evidence on the effect of subway openings on transportation patterns in figure 3. Levels of each transportation behavior variable clearly drop after each cutoff, although they are not dramatic relative to the underlying variation in the variables.

Daily bus ridership is basically flat in the 60 days prior to subway openings, but this traffic drops in the 60 days following. Although traffic congestion levels are much noisier, they also drop perceptibly after subway openings. Morning TCI also shows a large drop, and this drop is larger than that for evening TCI.

Generally speaking, these graphs align well with the findings from our discontinuity regressions, providing additional evidence that subway openings have an effect on transportation behavior. We test the robustness of our findings using a variety of alternative specifications below.

4.2 Expanded Sample Dates

We limited our sample window to 60 days in our main specification because of the dates of openings 4 and 5, which occurred just four months apart from each other. We can expand our sample period to an interval of six months before and after opening dates by dropping those two lines from consideration. These results are reported in table 6. In this table, we report the results of our testing from a variety of sample windows.

Our estimates of the effect of subway openings on congestion are generally confirmed by this alternative specification. Standard errors decrease as the window expands, because additional data improve the precision of the estimates. Coefficient magnitudes for congestion peak when the sample period is three months on either side of subway openings, and decline only slightly when the sample period is extended up to six months. Unlike the results in our 60-day specification, testing with larger sample windows suggests that subway openings do reduce evening congestion to a statistically significant degree. Generally, this additional evidence is highly supportive of our main findings: subway openings result in large decreases in congestion in the short-run.

Our estimates of the effect on subway traffic suggest that new subways do add to total subway traffic, but may also diminish traffic from existing lines. Estimates of the effect on bus traffic are less stable, with some estimates statistically indistinguishable from 0 over some sample windows.

4.3 Tests of Road Speed

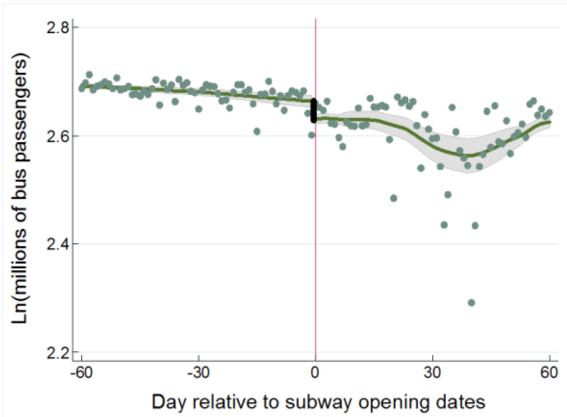
It would be useful to examine whether our findings on the effects on average Beijing congestion were observed in road speeds from individual roads in Beijing. We were able to obtain access to average road speed data for 22 roads in Beijing during the period September 1, 2014 through March 31, 2015. These data enable us to examine whether the openings of lines 7 and 14e, on December 28, 2014, increased average road speeds for these roads. We perform this test using equation (1), where the dependent variables are the natural logarithm of daily average road speed of a given road during morning rush hour and evening rush hour. We add the same covariates as rows 2 and 4 of table 4 in our specification, including a third order flexible polynomial.

We report the results of these regressions in figure 4. The X-axis of this figure is the distance from the midpoint of the road to either subway line 7 or subway line 14e, whichever is closer.

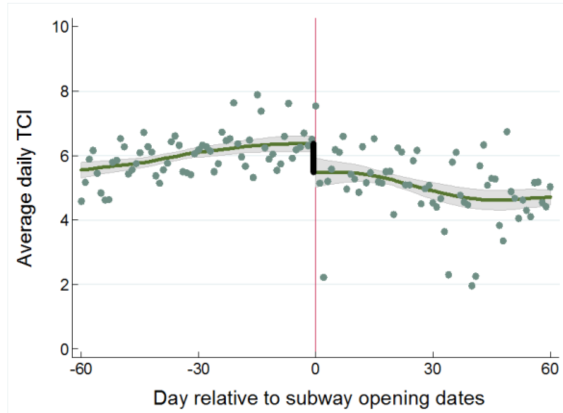
The top panel of this figure examines the effect of subway openings on morning average road speed. The point estimates are consistently positive, indicating that average road speeds tended to improve after the subway lines opened.

Figure 3. Outcome variables around subway opening dates

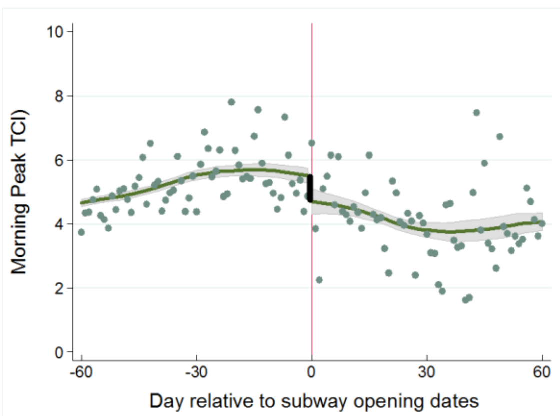
Panel A. Bus ridership



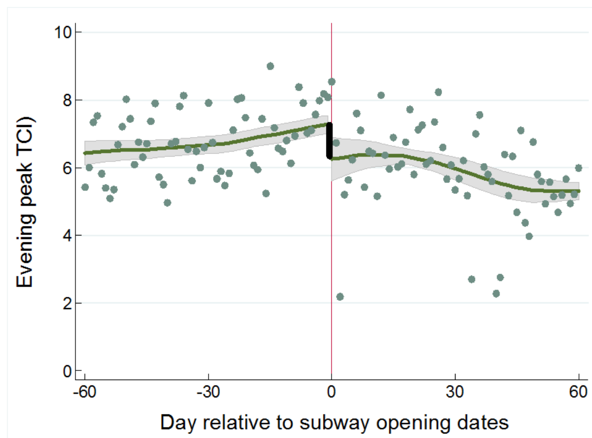
Panel B. Average daily TCI



C. Morning peak TCI



Panel D. Evening peak TCI



Notes: Each dot represents the average of the indicated variable across the five subway openings studied here. The trendline in each graph represents a 3rd order polynomial. Shaded areas represent 95% confidence intervals for the trendline. Weekends and holidays are dropped before taking averages for these graphs.

Table 6. R-D Results – Extended Sample Period without Openings 4 and 5

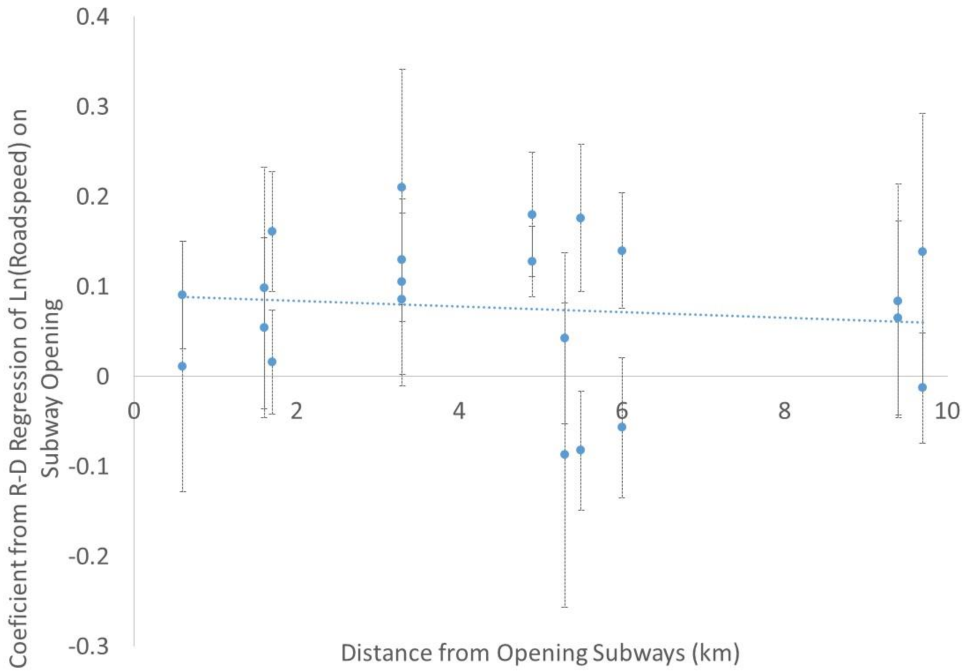
Dependent Variable	Ln(All SPV)	Ln(Existing SPV)	Ln(BPV)	TCI (all)	TCI (morning)	TCI (evening)
30 Days Around Opening (N = 157)						
Subway Open	0.084***	-0.014	-0.025**	-0.502	-0.320	-0.685
	[0.023]	[0.025]	[0.008]	[0.502]	[0.514]	[0.665]
R^2	0.974	0.981	0.862	0.576	0.728	0.515
60 Days Around Opening (N = 317)						
Subway Open	0.138***	0.030	-0.019	-0.721*	-1.240**	-0.207
	[0.015]	[0.019]	[0.013]	[0.349]	[0.445]	[0.345]
R^2	0.826	0.939	0.720	0.598	0.565	0.504
90 Days Around Opening (N = 473)						
Subway Open	0.067***	-0.047**	0.030	-1.082***	-1.569***	-0.597***
	[0.020]	[0.016]	[0.068]	[0.137]	[0.224]	[0.133]
R^2	0.860	0.942	0.120	0.514	0.460	0.461
120 Days Around Opening (N = 630)						
Subway Open	0.050***	-0.092***	-0.068**	-0.982***	-1.249***	-0.718***
	[0.017]	[0.016]	[0.031]	[0.132]	[0.199]	[0.122]
R^2	0.845	0.948	0.085	0.463	0.412	0.450
150 Days Around Opening (N = 791)						
Subway Open	0.085***	-0.063***	-0.074***	-0.828***	-1.177***	-0.482***
	[0.013]	[0.011]	[0.013]	[0.133]	[0.185]	[0.146]
R^2	0.823	0.941	0.099	0.367	0.382	0.373
180 Days Around Opening (N = 941)						
Subway Open	0.080***	-0.059***	-0.094***	-0.906***	-1.329***	-0.487***
	[0.015]	[0.008]	[0.012]	[0.137]	[0.189]	[0.157]
R^2	0.814	0.948	0.105	0.371	0.375	0.372

Notes: This table reports results of regressions of specification 4 from table 4. All regressions include a third-order polynomial in the predictor. Holidays and weekends are excluded from these models. Regressions with "covariates" contain weekday dummies, dummies for which license plates are excluded from Beijing roads that day, extreme weather dummies, and dummies for subway line. All standard errors are clustered using a dummy for the interaction of the weekday and which license plates are excluded that day.

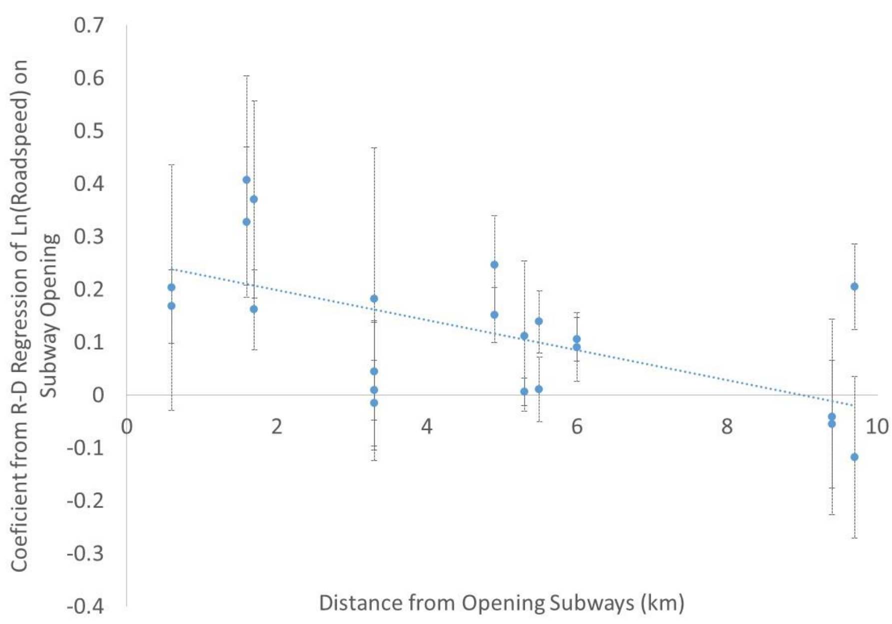
Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 4. R-D Regressions of Roadspeed on Subway Openings

Panel A. Morning Roadspeed



Panel B. Evening Roadspeed



Notes: Each dot represents the result of regressions of equation (1), where the dependent variable is the natural logarithm of average road speed of a road segment during morning rush hour or evening rush hour. Covariates in these regressions are the same as in specification 4 from table 4. The standard error of each regression is indicated by the error bar.

The bottom panel of this figure examines the impact of the subway openings on evening average road speed. Evening road speed of roads close to the subways tended to improve after subways opened, with a decaying effect as the distance between the road and the newly opened subway lines increases.

These results are basically supportive of our findings from sections 4.2 and 4.3. Morning road speeds overall do tend to increase, suggesting that the average decreases in TCI we found earlier are reflected at the individual road level. For evening traffic, increases in road speed are larger close to subways, but decay in roads farther away. This heterogeneity helps explain why the point estimates of the effect of subway openings are negative, but are statistically indistinguishable from zero in some specifications.

4.4 Alternative Specifications

In this section, we test the robustness of our results from our regression discontinuity specification. Our first concern involves the timing of subway openings: many openings coincide with holidays such as the calendar New Year. Although we drop holidays from our regressions, it is possible that travel around holidays is lower, because travelers leave Beijing early or end vacations late. We drop all observations within three days of a holiday, reasoning that the impact of most early departures or late returns is likely to occur within three days of holidays. We report our results in the first panel of table 7, using specification 4 from table 4. Dropping surrounding days appears to have limited effect on the basic narrative, with subway openings still playing a strong role substituting for bus traffic, and lowering average congestion and morning peak congestion.

Related to this concern, we address the possibility that seasonality in passenger volumes explain our results. We create four placebo comparison periods using other portions of daily travel behavior data available between 2009 and 2014. In each of these comparison periods, the dates match those of one of the six sample periods described in table 1, but they occur in years where no subway opening occurred. We include graphs summarizing these results in Appendix C. There is no discontinuity observed in the number of subway passengers, the bus passenger volume, or in any of our three measures of congestion. This placebo test supports the idea that subway openings rather than seasonality drive our RDD results.

We also address the possibility that other travel policies enacted in Beijing explain our results. For example, the Beijing license plate lottery began to curb the number of new cars, starting on January 1, 2011. In addition, a major adjustment of taxi fares occurred in June 2013. In this check, we remove subway openings 2 and 5 and re-estimate the model. Our results are reported in panel 2 of table 7. Again, the pattern of results is very similar.

We address the possibility that any single subway opening explains our results. We remove each subway opening in turn in panels 3 through 8 of table 7. The results are very similar, with decreases in congestion observed in every specification. The point estimate of the effect on evening peak traffic is negative in every specification, but not statistically significant.

We address the possibility that our results capture seasonality in travel behavior. This is of particular possible concern because government officials may want to take advantage of seasonal dips in transportation volume in order to artificially inflate the efficaciousness of subways on congestion. We augment our regression with weekly fixed effects. The benefit of this is allowing us to examine within-week variation due to subway openings, removing some seasonality from the data. The cost of this is that two of the six subway openings do not overlap weeks with the other four; as a result, we de-seasonalize only four of the six openings.

We report results in the last row of table 7. This specification largely confirms qualitatively our prior results: subway openings result in decreases in bus traffic and overall congestion. For many of the dependent variables, this specification actually increases the point estimate of the effect.

We next address the robustness of our main specification. Our main specification used 60 days on either side of new subway openings as the window; we vary this period to see whether smaller sample windows will affect our results. We first limit the sample to 30 days, then 45 days, and 60 days, and report our results in table 8.

The direction and general magnitude of our coefficients remains essentially intact as the sample window changes. The exception is bus traffic, which has an estimate statistically indistinguishable from zero when the sample window is 45 days. Standard errors expand as the sample shrinks because lower amounts of data adversely affect the precision of the estimates.

We also examine whether alternative polynomial forms affect our results in table 9. Our main specification relies on third-order polynomials, so we compare our results with other orders of polynomials. Qualitatively speaking, our main results hold true with each order of polynomial. Overall congestion and morning congestion drop significantly, while evening congestion is indeterminate.

5. Conclusion

We examine in this study how six subway openings in Beijing affect vehicle congestion. In our main specification, we find that reductions in congestion improve TCI by 0.728, reducing average daily driving delays by an average of 15% across the six openings. This result is robust across a broad set of specifications and potential alternative explanations. We also find that subway openings play an important role in reducing morning rush hour traffic.

All of these points combine to suggest that new subways lines can play an important role in reducing congestion in the short-term. Policy makers considering subway lines can take encouragement from the example of Beijing. We show how, while subways induce some substitution from buses, they also created clear reductions in overall congestion in the city. We also presented some evidence that increases in roadspeed in roads close to subways were observed.

Beijing's six subway openings that we study in this paper doubled the size of its subway system. Our results would be most externally valid in large, dense cities that have sparse subway systems in place and are considering expansions. China alone has 160 cities that have a population greater than 1 million people. Many other Asian cities also pair large populations with limited public transportation options.

Our results do not contradict the law of peak-hour congestion, which describes how traffic adjusts in the long run to loosened roads. The limitation of our empirical design, in which we focus on the levels of congestion immediately following subway openings, is an inability to study how traffic adjusts in the long run. Connecting our short run findings with the long run findings of the prior literature could be a useful area of future study.

Table 7. Regression Discontinuity-Based Results – Alternative Specifications Checks

	Ln(All SPV)	Ln(Existing SPV)	Ln(BPV)	TCI (all)	TCI (morning)	TCI (evening)
Excluding Days around Holidays (All subway openings)						
Subway Open	0.133***	0.041***	-0.025***	-0.722***	-1.242***	-0.218
(N = 420)	[0.010]	[0.003]	[0.006]	[0.153]	[0.275]	[0.149]
R^2	0.974	0.988	0.799	0.670	0.601	0.562
No Coinciding Travel Policies (Drops Openings 2 and 5)						
Subway Open	0.135***	0.033*	-0.017	-0.664*	-1.122**	-0.211
(N = 316)	[0.016]	[0.018]	[0.010]	[0.337]	[0.403]	[0.357]
R^2	0.840	0.939	0.732	0.641	0.598	0.535
Excludes Opening 1						
Subway Open	0.043	0.011	-0.030*	-0.498	-0.513	-0.493*
(N = 394)	[0.025]	[0.022]	[0.015]	[0.286]	[0.344]	[0.268]
R^2	0.616	0.764	0.600	0.668	0.612	0.618
Excludes Opening 2						
Subway Open	0.129***	0.030	-0.018*	-0.659*	-1.083**	-0.239
(N = 395)	[0.015]	[0.017]	[0.009]	[0.321]	[0.384]	[0.334]
R^2	0.847	0.941	0.718	0.614	0.582	0.516
Excludes Opening 3						
Subway Open	0.131***	0.036*	-0.016*	-0.722**	-1.113***	-0.339
(N = 395)	[0.015]	[0.017]	[0.007]	[0.316]	[0.358]	[0.316]
R^2	0.838	0.932	0.704	0.581	0.573	0.482
Excludes Opening 4						
Subway Open	0.130***	0.026	-0.020	-0.718*	-1.193**	-0.246
(N = 396)	[0.013]	[0.018]	[0.012]	[0.327]	[0.422]	[0.315]
R^2	0.837	0.943	0.707	0.555	0.542	0.471
Excludes Opening 5						
Subway Open	0.122***	0.031*	-0.022**	-0.733**	-1.155***	-0.320
(N = 396)	[0.014]	[0.016]	[0.010]	[0.315]	[0.378]	[0.313]
R^2	0.823	0.924	0.680	0.602	0.576	0.502
Excludes Opening 6						
Subway Open	0.135***	0.031**	-0.031***	-0.946**	-1.497***	-0.405
(N = 399)	[0.020]	[0.014]	[0.005]	[0.323]	[0.360]	[0.366]
R^2	0.884	0.917	0.518	0.576	0.561	0.467
Includes Week FE						
Subway Open	0.075**	-0.025	-0.039***	-1.207**	-1.084**	-1.333*
(N = 475)	[0.035]	[0.023]	[0.010]	[0.530]	[0.479]	[0.678]
R^2	0.866	0.944	0.763	0.704	0.715	0.636

Notes: This table reports results of regressions of equation (1) when the dependent variable is bus passenger volume (BPV), subway passenger volume (SPV), or the traffic congestion index (TCI). The reported coefficient in each cell is the coefficient on "Subway Open," a dummy variable indicating whether the new subway line had opened. All regressions are based on model specification 4 of table 4, and include a third order polynomial. All standard errors are clustered using a dummy for the interaction of the weekday and which license plates are excluded that day.

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. R-D Results – Sample Window Tests

Dependent Variable	Ln(All SPV)	Ln(Existing SPV)	Ln(BPV)	TCI (all)	TCI (morning)	TCI (evening)
30 Days Around Opening (N = 236)						
Subway Open	0.073***	-0.008	-0.028***	-0.733	-0.445	-1.034*
	[0.018]	[0.019]	[0.006]	[0.432]	[0.464]	[0.525]
R^2	0.969	0.982	0.837	0.512	0.654	0.464
45 Days Around Opening (N = 355)						
Subway Open	0.130***	0.045*	0.004	-0.646*	-0.723	-0.578
	[0.021]	[0.023]	[0.011]	[0.354]	[0.413]	[0.453]
R^2	0.920	0.942	0.749	0.531	0.580	0.434
60 Days Around Opening (N = 475)						
Subway Open	0.117***	0.028*	-0.023**	-0.728***	-1.120***	-0.343
	[0.013]	[0.016]	[0.009]	[0.302]	[0.362]	[0.295]
R^2	0.830	0.927	0.668	0.578	0.562	0.485

Notes: This table reports results of regressions of specification 4 from table 4. All regressions include a third-order polynomial in the predictor. Holidays and weekends are excluded from these models. Regressions with "covariates" contain weekday dummies, dummies for which license plates are excluded from Beijing roads that day, extreme weather dummies, and dummies for subway line. All standard errors are clustered using a dummy for the interaction of the weekday and which license plates are excluded that day.

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9. Regression Discontinuity Robustness Check – Other Order Polynomials

	Ln(All SPV)	Ln(Existing SPV)	Ln(BPV)	TCI (all)	TCI (morning)	TCI (evening)
1st order polynomial						
Subway Open	0.102***	0.018	-0.029***	-0.799**	-1.169***	-0.437
	[0.014]	[0.017]	[0.010]	[0.301]	[0.360]	[0.296]
R^2	0.792	0.911	0.594	0.427	0.509	0.318
2nd order polynomial						
Subway Open	0.116***	0.024	-0.023**	-0.696**	-1.100***	-0.300
	[0.013]	[0.017]	[0.009]	[0.289]	[0.354]	[0.279]
R^2	0.828	0.918	0.668	0.535	0.548	0.436
3rd order polynomial (Baseline)						
Subway Open	0.117***	0.028*	-0.023**	-0.728**	-1.120***	-0.343
	[0.013]	[0.016]	[0.009]	[0.302]	[0.362]	[0.295]
R^2	0.830	0.927	0.668	0.578	0.562	0.485
5th order polynomial						
Subway Open	0.113***	0.023	-0.025***	-0.734**	-1.112***	-0.364
	[0.014]	[0.015]	[0.007]	[0.305]	[0.360]	[0.307]
R^2	0.840	0.932	0.686	0.625	0.593	0.522
7th order polynomial						
Subway Open	0.091***	0.011	-0.029***	-0.888***	-1.120***	-0.665**
	[0.011]	[0.012]	[0.004]	[0.295]	[0.350]	[0.306]
R^2	0.846	0.934	0.719	0.652	0.625	0.562
9th order polynomial						
Subway Open	0.091***	0.011	-0.029***	-0.885***	-1.124***	-0.656*
	[0.011]	[0.012]	[0.004]	[0.297]	[0.350]	[0.307]
R^2	0.847	0.934	0.719	0.653	0.625	0.565
11th order polynomial						
Subway Open	0.089***	0.012	-0.034***	-0.817**	-0.983**	-0.663*
	[0.013]	[0.012]	[0.005]	[0.291]	[0.334]	[0.313]
R^2	0.847	0.934	0.721	0.654	0.630	0.565

Notes: This table reports results of regressions of equation (1) when the dependent variable is bus passenger volume (BPV), subway passenger volume (SPV), or the traffic congestion index (TCI). The reported coefficient in each cell is the coefficient on "Subway Open," a dummy variable indicating whether the new subway line had opened. All specifications are similar to that of specification 4 of table 4. Standard errors are clustered using a dummy for the interaction of the weekday and which license plates are excluded that day.

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

References

Adler, M. W., and J. N. van Ommeren. 2016. Does public transit reduce car travel externalities? Quasi-natural experiments' evidence from transit strikes, *Journal of Urban Economics* 92: 106-119.

Anderson, M. L. 2014. Subways, Strikes and Slowdowns: The Impact of Public Transit on Traffic Congestion, *American Economic Review* 104 (9):2763-2796.

Beaudoin, J., Y. H. Farzin, and C.-Y. C. L. Lawell. 2015. Public transit investment and sustainable transportation: A review of studies of transit's impact on traffic congestion and air quality. *Research in Transportaion Economics* 52: 15-22.

Centre for Economics and Business Research. 2014. The future economic and environmental costs of gridlock in 2030.

Chen, Y., and A. Whalley. 2012. Green Infrastructure: The Effects of Urban Rail Transit on Air Quality. *American Economic Journal: Economic Policy* 4(1): 58-97.

Davis, L.W. 2008. The Effect of Driving Restrictions on Air Quality in Mexico City. *Journal of Political Economy* 116(1): 38-81.

Downs, A. 1962. The Law of Peak-Hour Expressway Congestion. *Traffic Quarterly* 16(3): 393-409

Duranton, G., and M. Turner. 2011. The Fundamental Law of Road Congestion: Evidence from US Cities. *American Economic Review* 101(6): 2616-2652.

Gelman, A., and G. Imbens. 2017. Why high-order polynomials should not be used in regression discontinuity designs. *Journal of Business & Economic Statistics* 0(0). http://dx.doi.org/10.1080/07350015.2017.1366909

Parry, I., and K.A. Small. 2005. Does Britain or the United States Have the Right Gasoline Tax? *American Economic Review* 95(4): 1276-1289.

Winston, C., and A. Langer. 2006. The Effect of Government Highway Spending on Road Users' Congestion Costs. *Journal of Urban Economics* 60(3): 463-483.

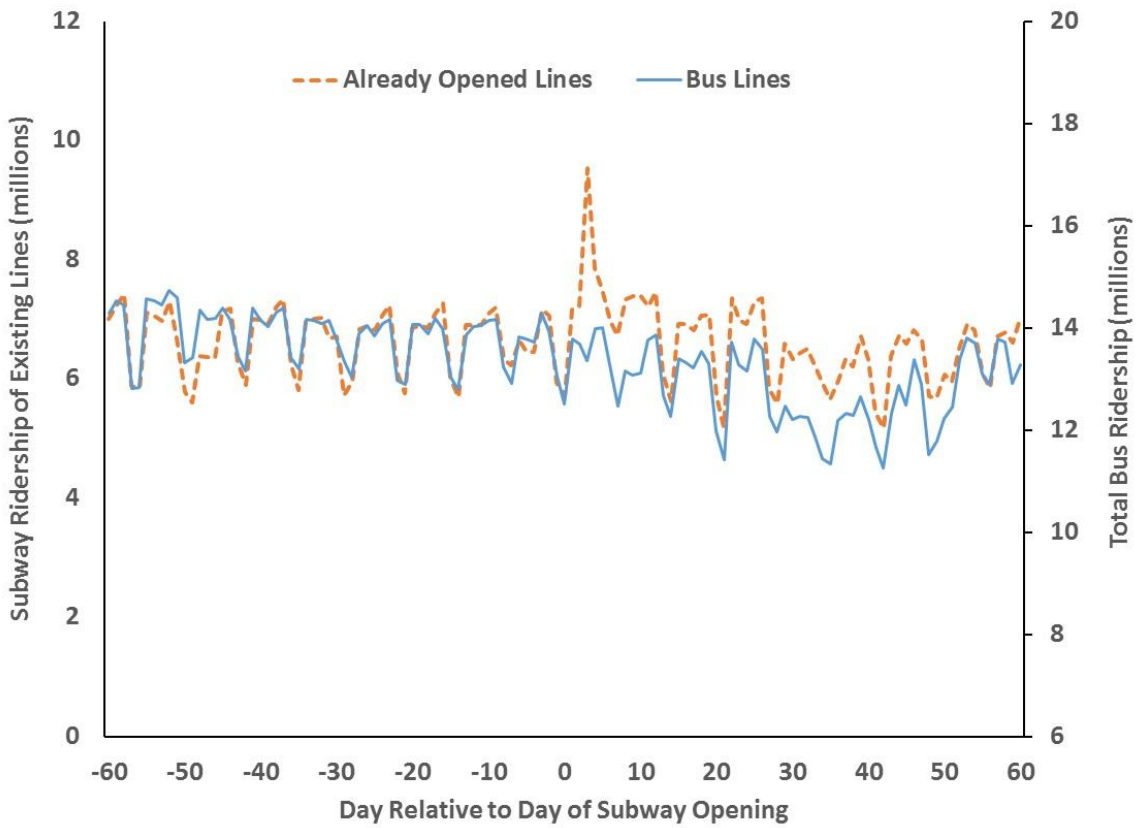
Yang, J., Y. Liu, P. Qin, and A. Liu. 2014. A Review of Beijing's Vehicle Lottery: Short-term Effects on Vehicle Growth, Congestion, and Fuel Consumption. *Energy Policy* 75: 157-166.

Appendix A. Explanation of Drops in Bus Passenger Volume.

Table 2 suggests that subway passenger volume rises by about 0.25 million, while bus passenger volume drops by 1.1 million passengers. Lacking individual ridership data taken around the time of each subway opening, we cannot resolve this apparent discrepancy perfectly. However, we can offer our best analysis as to the disparity.

We first plot bus ridership in the same manner as figure 2:

Figure 2. Ridership on the Beijing subway system near subway openings



Notes: This chart represents the average of the 6 subway line openings we explore in this paper. We exclude holidays in this graph. The X-axis represents the number of days from the opening of the new lines.

Before the six subway openings, bus ridership tracks total subway ridership very closely, with the trends in seasonality bearing a striking resemblance. However, after subway openings, bus ridership appears to decline while ridership on existing lines is essentially flat. Because bus ridership is roughly double that of subway riders, this decline is large and averages more than one million riders per day in the post-opening periods.[16]

[16] This graph is consistent with the hypothesis in the paper that subway openings cause changes in bus ridership; declines in bus ridership coincide almost exactly with subway opening dates.

So why would the decline in bus ridership (-1.1 million) be so much greater than the gain in subway ridership (+0.25 million)?

The root of our explanations stems from the manner in which the data are collected. Our data on bus and subway ridership in this paper reflect the number of card swipes as riders pay for their transportation. In the Beijing system during the time of these data, a swipe occurred only once for each subway rider. That subway rider may transfer between lines an unlimited number of times, and s/he still pays once and counts as one passenger. However, a passenger must swipe each time s/he changes buses. If the passenger transfers between buses, s/he will swipe a farecard for each bus, and count as multiple passengers.

Because of this counting system, two effects will multiply the apparent effect on bus traffic when new subway lines open. First, one new subway trip can replace multiple bus trips. Second, trips that were mixed between bus and subway use that are changed to subway-only through the subway line extension will reduce the number of bus passengers without increasing the number of subway passengers.

To show the first effect, suppose that a passenger, instead of taking two buses, now takes a subway between his/her origin and destination. Each new subway passenger will decrease the number of bus passengers by two. However, this explanation alone would explain only a part of the large multiple between -1.1 million bus passengers and +0.25 million subway passengers.

The second effect is likely to be even larger. Suppose that, before the subway line opened, a passenger took a subway to a given point, and then took a bus from that point to his destination. This passenger would be counted as one subway passenger and one bus passenger. Suppose that the subway extension opens a new stop close to the destination of the passenger, allowing this passenger to take the subway all the way to his/her destination. The person making the same trip would now be counted as just one subway passenger.

As a result, the subway line opening would decrease bus passenger volume without increasing the number of subway card swipes. If a significant fraction of the 6-7 million subway passengers on existing lines also take the bus before the subway opening and do not take the bus after, we would see that fraction be removed from bus passenger volume with no increase in subway passenger volume.

To check whether our explanations are plausible in individual-level data, we leverage trip diaries collected in Beijing. In trip diaries, surveyed individuals report each leg of their journey. For example, a person might report walking to the subway, taking the subway a given distance, and then taking the bus to their destination. In these data, each leg shows up separately during the same trip, avoiding the swipe problem above. We have two sets of trip diaries available that are relevant to this project: one taken between September and October 2010 (between subway openings 1 and 2) and one taken between September and November 2014 (between subway openings 5 and 6).[17] We will call the earlier trip diary "Trip Diary 1" and the later trip diary "Trip Diary 2."

[17] The ideal dataset would be travel diaries with some entries taken immediately before a subway opening and some taken immediately after an opening. Unfortunately, this dataset does not exist in our knowledge.

In the following statistics, we aggregate all modes of travel into one trip. For example, if a person commutes to work by driving to a subway station and then taking a subway to work, we count that as one trip where a car and subway were both used.

As context, we first report the percentage of all trips involving a bus or subway below:

	Trip Diary 1 (9/10 – 10/10)	Trip Diary 2 (9/14 – 11/14)
Percentage of Trips where Bus was Taken	21.2%	16.7%
Percentage of Trips where Subway was Taken	5.3%	5.9%

This table suggests that bus ridership declined in importance while subway ridership is rising in importance in Beijing travel behavior during this period.

In support of the first explanation, we examine the number of passengers who take the bus multiple times during a single trip. In Trip Diary 1, 23.3% of all passengers taking a bus during a trip took 2 or more buses during that trip. In Trip Diary 2, only 18.8% of all bus passengers took 2 or more buses. This suggests that, during this period of multiple subway openings 1) taking multiple buses on a single trip is common in Beijing and 2) over the period during which subways opened, the fraction of multiple bus trips declined.

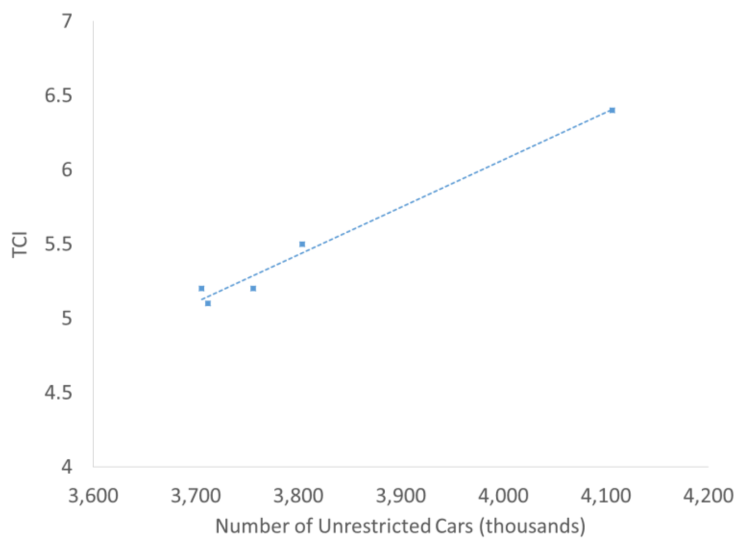
In support of the second explanation, we examine the fraction of trips that are mixed between subway and bus. We find that, in Trip Diary 1, 47.0% of all trips where the passenger takes the subway also involve taking the bus. However, in Trip Diary 2, only 37.9% of all subway passengers take the bus. This suggests that 1) double counting using card swipe data is very common, with a large number of subway passengers also counted in bus passenger statistics and 2) during the period between the two trip diaries, the fraction of subway passengers who were double counted as bus passengers fell sharply. This would result in large falls in bus card swipe counts, even without raising the number of subway swipe counts.

Appendix B. Comparison of Results to Driving Restrictions Based on Vehicle License Plate Number

In Beijing, driving is restricted one day per week during rush hours based on the trailing digit of one's license plate. Since Chinese people are superstitious about the number "4," which is homonymous with "death" in Chinese, there are fewer plates with the trailing digit "4." As a result, each weekday has a different number of unrestricted vehicles; on days where license plates with the trailing digit "4" are restricted, there are more unrestricted vehicles.

We present a figure correlating the number of unrestricted vehicles in Beijing with the average TCI for those weekdays in 2013 in the below figure:

Appendix B, Figure 1. The Correlation Between the Number of Registered Cars with a Given Trailing Digit and Average Daily TCI (2013)



The dot on the far right of this figure are days where license plates with the trailing digit "4" are restricted. The trendline on this graph suggests that there is a positive correlation between the number of unrestricted cars and congestion. The slope of this trendline is 0.0032, implying that an increase of 100,000 cars is associated with a 0.32 increase in daily average TCI.

In our central specification, 254,000 subway riders on average are added to newly opened subway lines. Subway openings cause a drop in TCI of 0.728 in our central specification. If all subway riders came from cars, a 100,000 decrease in the number of cars would be associated with a (0.728/254,000*100,000) = 0.29 increase in daily average TCI.

We caution that the figure connecting vehicles not restricted by license plate restrictions and TCI reveals simple correlations, and is not the result of well-identified regression analysis. However, it shows that the magnitude of our estimates from our R-D framework are quantitatively plausible.

Appendix C. Placebo Tests for Seasonality.

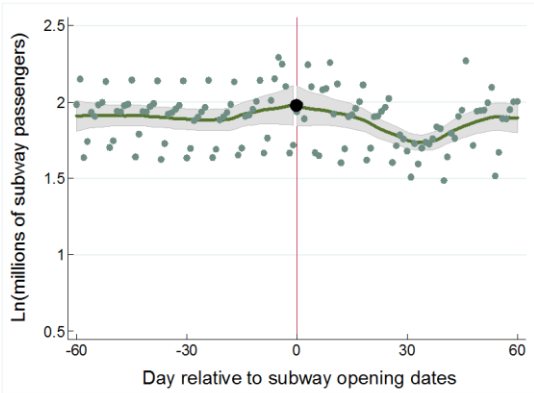
One form of placebo check that we can do is to examine comparison periods that have dates which match the sample periods from table 1, but occur in years where no subway was opened. Since available data are limited to between 2009 and 2014, we are only able to create four comparison periods to match the six subway openings. Comparison periods are described in the following table:

Subway Opening	Subway Lines	Opening Date	Sample Period	Period for comparison
1	Line 4	9/28/2009	7/30/09 – 11/27/09	7/30/10 – 11/27/10
2	Lines 15, CP, DX, FS, YZ	12/30/2010	10/31/10 – 2/28/11	10/31/09 – 2/28/10
3	Lines 8, 9	12/31/2011	11/1/11 – 2/29/12	N/A
4	Line 6	12/30/2012	10/31/12 – 2/28/13	10/31/13 – 2/28/14
5	Line 14	5/5/2013	3/6/13 – 7/4/13	3/6/12 – 7/4/12
6	Lines 7, 14e	12/28/2014	10/29/14 – 2/26/15	N/A

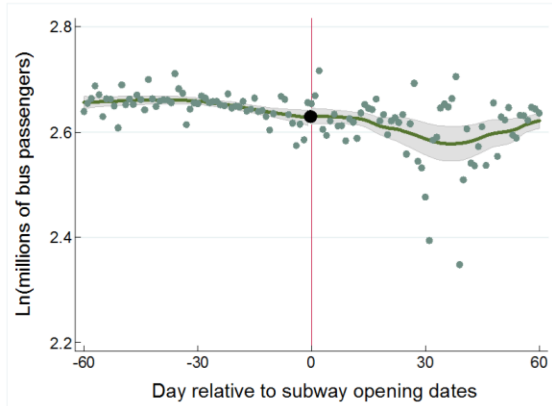
We then reproduce figure 3 using these comparison periods in Appendix C, Figure 1. The broad seasonality trends of figure 3 are present in these graphs, such as the dip in passenger volume occurring in the region 30 to 40 days after subway openings. As discussed in the paper, this dip is caused by the Chinese Lunar New Year, the most important holiday in China. However, we see no discontinuity present during the subway opening dates in these comparison periods.

Appendix C, Figure 1. Outcome variables during placebo comparison periods

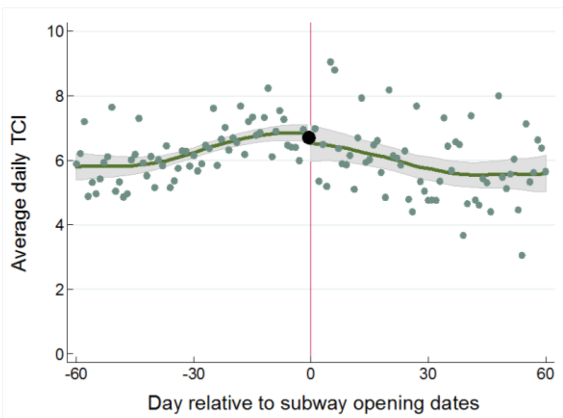
Panel A. Subway ridership



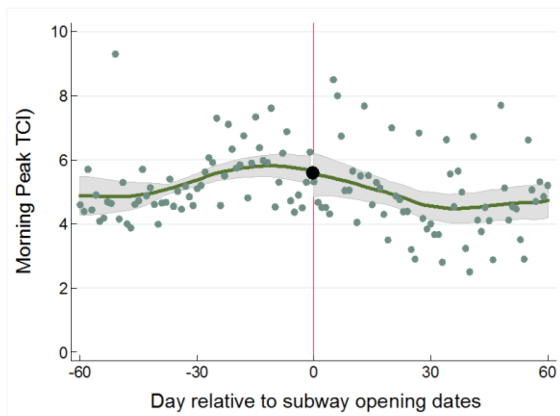
Panel B. Bus ridership



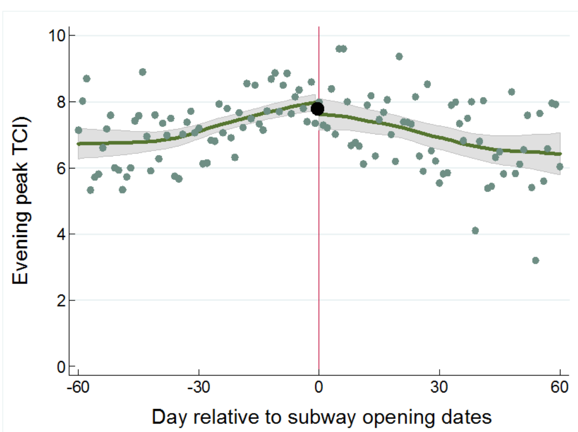
Panel C. Average daily TCI



Panel D. Morning peak TCI



Panel E. Evening peak TCI



Notes: Each dot represents the average of the indicated variable across the four subway openings studied here. The trendline in each graph represents a 3rd order polynomial. Shaded areas represent 95% confidence intervals for the trendline. Weekends and holidays are dropped before taking averages for these graphs.

Appendix D. Main Results with Different Types of Standard Error Clustering

In our main specification, we cluster our standard errors using the interaction of the day of the week and which license pair is banned on that day. These standard errors reflect Beijing's transportation patterns, as explained on page 9. However, there may be other forms of between-day correlation in travel demand, so we explore several alternative methods for standard errors to ascertain whether our results are robust to the form of clustering chosen.

We can see from this table that the statistical significances of our results are basically unchanged with the type of standard error chosen. No single method consistently produces the largest standard error, although clustering by month produces the largest for several of the outcome variables.

Appendix D Table. Regression Discontinuity-Based Results with Alternative Standard Errors

Dependent Variable	Ln(All SPV)	Ln(Existing SPV)	Ln(BPV)	TCI (all)	TCI (morning)	TCI (evening)
Specification 1: Clustered by the interaction of day of week with license plate pair						
Subway Open	0.117***	0.028*	-0.023***	-0.728***	-1.120***	-0.343
	[0.013]	[0.016]	[0.009]	[0.302]	[0.362]	[0.295]
R^2	0.830	0.927	0.668	0.578	0.562	0.485
Specification 2: Newey-West Standard Errors						
Subway Open	0.117***	0.028*	-0.023***	-0.728***	-1.120***	-0.343
	[0.018]	[0.015]	[0.008]	[0.234]	[0.236]	[0.323]
Specification 3: Clustered by month						
Subway Open	0.117***	0.028	-0.023***	-0.728**	-1.120**	-0.343
	[0.054]	[0.027]	[0.012]	[0.257]	[0.389]	[0.442]
R^2	0.830	0.927	0.668	0.578	0.562	0.485
Specification 4: Clustered by week						
Subway Open	0.117***	0.028	-0.023***	-0.728***	-1.120***	-0.343
	[0.036]	[0.025]	[0.013]	[0.250]	[0.312]	[0.418]
R^2	0.830	0.927	0.668	0.578	0.562	0.485
Specification 4: Clustered by the interaction of month and week						
Subway Open	0.117***	0.028	-0.023***	-0.728***	-1.120***	-0.343
	[0.036]	[0.025]	[0.013]	[0.248]	[0.307]	[0.414]
R^2	0.830	0.927	0.668	0.578	0.562	0.485
(N = 475) for all regressions						

Notes: This table reports results of regressions of equation (1) when the dependent variable is bus passenger volume (BPV), subway passenger volume (SPV), or the traffic congestion index (TCI). "All SPV" refers to total subway passenger volume, and "Existing SPV" refers to subway passenger volume less that added on the newly opened lines. The reported coefficient in each cell is the coefficient on "Subway Open," a dummy variable indicating whether the new subway line had opened.
All regressions correspond to specification 4 in table 4, so include a third-order polynomial in the predictor, with covariates for weekday dummies, dummies for which license plates are excluded from Beijing roads that day, extreme weather dummies, and dummies for subway line. Holidays and weekends are excluded from these models.

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.