

Congestion and pollution consequences of driving-to-school trips: A case study in Beijing



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ABSTRACT

Parents compete for high-quality education for their children by enrolling them in good schools. However, in a Chinese mega-city like Beijing, three factors jointly lead to the spatial separation between schools and homes: the centralized public goods provision mechanism, the historical dependency in school location, and the constrained supply of housing in downtown. Without an adequate number of school buses, this spatial separation of schools and homes triggers the numerous long-distance driving-to-school trips by private vehicle during weekday morning rush hours in Beijing. We use the start and end dates of “school holiday” as exogenous repeated shocks to the aggregate traffic congestion, and employ the two-stage least squares (2SLS) regression approach to examine the congestion and pollution consequences of such driving-to-school trips in Beijing. We find that, all else being equal, workdays during school holidays have a traffic congestion index 20% lower than that of non-school-holiday workdays. Such a sharp reduction in congestion leads to a significant decrease in PM₁₀ concentration. Policymakers should lower such “extra” congestion and environmental costs via optimizing the spatial balance between school supply and demand.

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1. Introduction

During the past decades, rapid growth of car ownership and usage, combined with lagged transportation infrastructure supply, have led to serious traffic congestion in China's large cities. According to the data released by the Beijing Transportation Research Center, the number of private cars grew from 1.34 million in 2005 to 3.57 million in 2010, the one-way commuting time for Beijing residents also increased from 37 min to 44 min in the same period (Meng, 2011). A rough estimation shows that fifteen Chinese cities at the top of the traffic congestion list suffer totally 1 billion yuan loss every day in terms of the travel time wasted on roads.¹ As another social cost of rapid motorization, vehicle exhaust emission makes a significant contribution to air pollution in Chinese megacities.² In Beijing, it accounts for 31.1% of PM_{2.5} emissions from local sources, and this proportion is larger than any other source.³ Therefore, how to effectively manage the traffic congestion and air

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URL: <http://www.siqizheng.cn> (S. Zheng).

¹ http://www.china.org.cn/top10/2012-11/02/content_26980425.htm.

² Source: <http://www.globaltimes.cn/content/915067.shtml>.

³ See details in this report: http://greeninitiatives.cn/img/white_papers/14368662921811.pdf.

pollution consequences of private car transportation has become an enormous challenge for those cities (Chen et al., 2013; Zheng and Kahn, 2013).

Traffic congestion and related pollution issues are closely related to urban land use patterns. Commuting trips between home and workplace as well as related jobs-housing balance issue have been widely investigated. However, in recent years, transportation surveys in developed cities have documented the rising importance of non-commuting trips. Like many large cities in the US, Beijing has also experienced a declining proportion of commuting trips and it was already below 40% by 2010.⁴ Within the various non-commuting trips in large Chinese cities, many are driving-to-school trips by urban residents. During the rapid expansion of the cities, many people have moved out of downtown, where the traditional quality schools are still located. The institutional arrangements have caused the spatial separation between where households live and where their children attend schools. In the absence of school bus system, this spatial separation generates a considerable amount of school trips via decentralized private driving in Chinese cities. Based on the 4th Beijing Comprehensive Transportation Survey (in 2010), our rough calculation of aggregate effect shows that driving-to-school trips account for about 15% of all the trips in morning rush hours on a typical workday.⁵ This can explain the sharp jump in the city's traffic congestion level on the first school day after the school holiday, and a sharp drop on the first school holiday.⁶ For example, Yang et al. (2016) calculates that the average speed of two selected routes on school days was 29.6% higher than that during summer school holidays in 2013.

Taking Beijing as a case, this paper aims to answer the following empirical question: How do drive-to-school trips, regarded as the result of spatial separation between schools and households, significantly contribute to the aggregate traffic congestion in Beijing's urban road network, and further aggravate air pollution? To answer this question, we take advantage of the start/end dates of school holidays as repeated exogenous shocks to extract the congestion effect of driving-to-school trips in the morning rush hours. Two-stage least squares (2SLS) regression approach is employed to further investigate if the "chain" channel in "driving-to-school trips– congestion – pollution" does exist.

The remainder is organized as follows. Section 2 reviews some relevant previous literature. Section 3 introduces the institutional background for the spatial separation of schools and households and the popularity of driving-to-school trips in Beijing. Section 4 presents data and the empirical strategy we use in this study. Section 5 presents regression results of the two-stage least squares regressions and robustness checks. Section 6 concludes.

2. Literature review

Numerous urban and transportation studies have suggested the importance of urban spatial structure for travel behaviors. As the dominant model of urban spatial structure, the monocentric city model of Alonso (1974), Mills (1967) and Muth (1969) (AMM) captures the fundamental trade-off in residential location choice between central-city oriented commuting cost and housing consumption. More recently, studies on "wasteful commuting" have argued that real commuting time and distances are much greater than those predicted by the simple AMM model, even if job decentralization is considered (Hamilton and Röell, 1982; Hamilton, 1989; Small and Song, 1992). These recent studies show that several important factors violate the AMM model's assumption of the above trade-off between commuting cost and housing cost. Those factors include the increasing number of two-worker households, job uncertainty and heterogeneity, as well as non-commuting trips to shops, schools and other amenities. This means that planning or policies aiming at solely a "jobs-housing balance" will only have a limited effect of mitigating congestion and pollution (Giuliano and Small, 1993). Researchers have advocated for the importance of including the location and accessibility of urban amenities, such as schools, in residential locational choice and travel mode choice models (Ewing et al., 2004; Ng, 2008; Wilson et al., 2010; Yang et al., 2012). In another stream of the literature, referred to as Tiebout (1956) theory, urban residents are considered to "vote with their feet" for the provision of local public goods. Oates (1969) and many subsequent studies further focus on demand for education services among communities, and Rosen (1974)'s hedonic price technique is widely employed to estimate residents' willingness-to-pay for quality education (Black and Machin, 2011; Feng and Lu, 2013).

The recent studies have explored the effects of urban spatial patterns on commuting, and consequently, on environmental quality. The expansion of urban space, the population density, the reliance on automobiles and the commuting distance may affect urban environment (Anderson et al., 1996; Kahn and Mills, 2006; Chen et al., 2008). Different patterns of urban expansion also have different congestion and environmental impacts (Camagni et al., 2002; Lohrey and Creutzig, 2016; Duranton and Turner, 2016). On the one hand, numerous transportation and environmental science studies have analyzed the contribution of automobiles on congestion and air pollution during the process of suburbanization (Liu et al., 2008; Zhao, 2010; Walsh, 2014); on the other hand, some urban studies have investigated that the compactness of urban space may reduce the energy consumption of vehicles and pollution (Glaeser and Kahn, 2010; Gaigné et al., 2012). The existing literature mainly focuses on the effects of the accessibility of employment and infrastructure on commuting and environment (Gordon et al., 1989; Peng, 1997; Cirilli and Veneri, 2014; Zhou et al., 2016). However, few literature has paid attention to the accessibility of public services and how it affects aggregate congestion and pollution.

Several recent papers examine the congestion and pollution issues from another perspective – the impacts of the various transport policies on road congestion and air quality, different empirical strategies are employed in previous studies (Beevers

⁴ Source: 4th Beijing Comprehensive Transportation Survey.

⁵ The estimation procedure is available upon request.

⁶ Traffic congestion index is published by Beijing Transportation Research Center (see details in Section 4).

and Carslaw, 2005; Sun et al., 2014; Viard and Fu, 2015). A big challenge such studies face is the endogeneity between congestion and air pollution when using the naïve OLS regression technique – for instance, people will drive more (to protect themselves against the dirty air) or less (staying at home) on polluted days (Currie et al., 2009).

Building on the existing literature, this paper may contribute to urban congestion and environment studies in two aspects. First, this is one of the first efforts empirically examine how the public service-housing separation affects aggregate congestion and, consequently, air pollution. Second, using school holidays as repeated exogenous events and the instrument variables, the endogeneity bias in the estimation of causal relationship between congestion and pollution is mitigated.

3. Institutional background

In contrast to the United States and many other developed nations, there is no real “property tax” in China, urbanites have little say over local public budgeting. In addition, Chinese urbanites do not elect local governments. The provision of local public goods is a centralized decision, mainly relying on local public finance, and it does not effectively respond to various demands from households in decentralized neighborhoods.

As typical local public goods, primary and secondary schools are almost all constructed and maintained by the municipal governments in Chinese cities, and more than 95% of students enter those public schools.⁷ According to China’s “school attendance zone policy”, homeowners in a school’s “school attendance zone” are eligible to send their children to that school for a standard, but quite low, fee. However, this does not mean households have the only choice to enroll their children in the nearby school or must physically live in the corresponding school attendance zone. Many middle-class parents believe that studying at a good school is crucial for their children to receive high-quality education and to own a bright future. Those parents (especially the rich ones) compete for good schools and have various means to send their children to a good school even if they do not reside in the corresponding school zone, such as paying a large school admission fee without owning a housing unit there (Zhou and Lu, 2009), passing special admission tests organized by a good school, etc. (Zheng et al., 2015). Besides, some households purchase old or small housing units in good school zones but do not actually live there. Instead, they lease those units out or just keep the units vacant, and they live in a larger house or somewhere with better living conditions outside the corresponding school zone. Therefore, a considerable proportion of students live outside their school zones.

The municipal governments have not paid sufficient attention to the spatial mismatch of school quality and housing supply for a long time. Here we take Beijing as an example. Most of the public schools were built intensively before the 1980s, and the high-quality ones were clustered in the inner city when the urban area was quite small. Further government funding for public education could maintain the operation of the original good schools but could not finance building many new ones (especially good ones) during the rapid urban expansion. Therefore, good schools in monocentric Beijing have not changed significantly either in number or location, which does not match the ongoing suburbanization of urban households. Moreover, the restriction of land supply and new housing construction in Beijing downtown area further exacerbate the spatial separation of good schools and households (Zheng and Kahn, 2008). As Fig. 1 shows, the density of all primary schools in inner-city Beijing (downtown, the area within the 3rd ring road) is much higher than that in the outer city, and the inner-outer ratio is higher than the population density ratio. Furthermore, the inner city, where 63.8% of all the highest-quality primary schools (“key” schools⁸) are located, enjoys a much higher density of these key schools than the outer city.

Due to the spatial mismatch between school quality and housing supply (both quantity and quality), many medium- and high-income households choose to live where the housing supply is elastic and better living quality exists, while sending their children to high-quality schools in other school zones. Yu and Liu (2011) investigate three key primary schools in Beijing and report that 53.3% of students live outside the school zones (about 2 km radius of these schools). Thus, long-distance trips to schools are quite common in Beijing, while taking a school bus is not a preferred way to transport students to schools. Overall, fewer than 3% of students in Beijing take school buses.⁹ To ensure that their children have a safe and comfortable trip, many parents choose to send their children to school by private car.

4. Data and empirical strategy

4.1. Data

It is extremely difficult to obtain individual’s travel diary data in Chinese cities because such data is not publicly available. Therefore, we could not use micro data to provide the direct evidence showing how the spatial mismatch of schools and housing affects parents’ driving-to-school behaviors at different locations. Instead, our empirical study identifies the aggre-

⁷ The number of private schools are very limited. According to the Beijing Municipal Commission of Education, out of a total of 1160 primary schools in 2010, only 24 were private schools. Those private schools mainly serve expats and households considering sending their children overseas for high school and/or college.

⁸ Key schools, so-called excellent schools, are the highest-quality schools in Chinese cities. These schools have much better education quality and receive much stronger public financial support than other good schools. According to statistics, roughly 5–10% of all schools in Beijing are key schools. The list of such “key schools” is released by Beijing Municipal Commission of Education, and is the local common knowledge to Beijing residents. However, the exact exam scores and other quantitative school quality measures are not publicly available.

⁹ Source: 4th Beijing Comprehensive Transportation Survey.

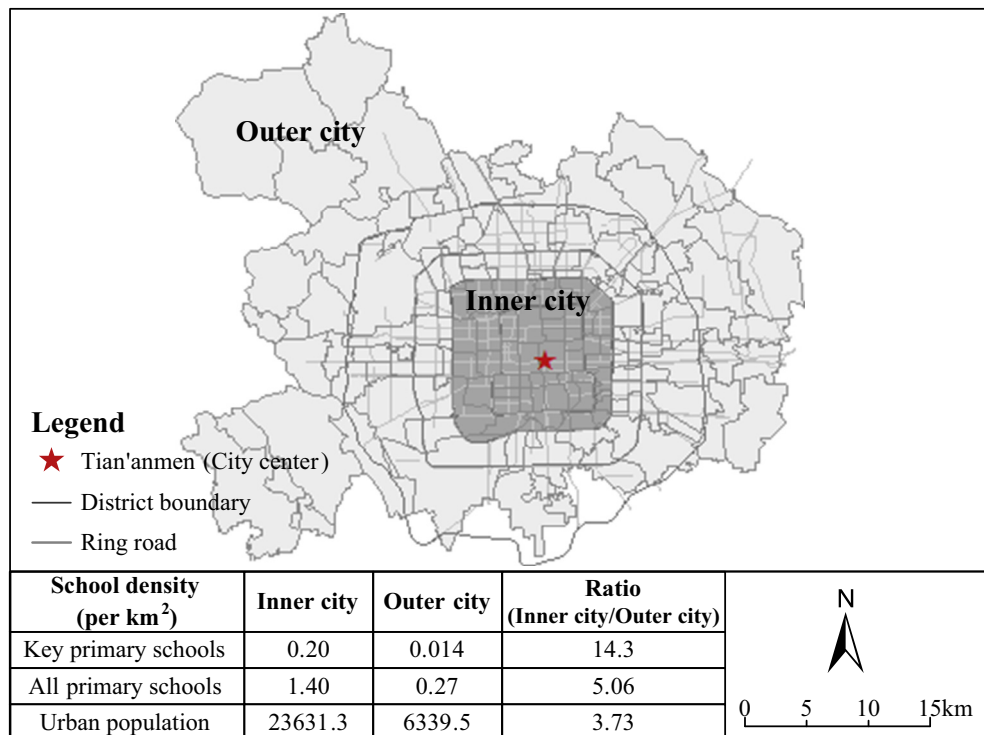


Fig. 1. Spatial distributions of primary schools and urban population. Data Source: Beijing Municipal Commission of Education; 2010 Beijing Population Census database.

gate effects of driving-to-school trips by analyzing the temporal variations of city-level traffic congestion and air pollution. We examine whether traffic congestion and air pollution significantly change around the start/end dates of school holidays. Here we introduce the key data sets we use in this study.

4.1.1. School calendar

The school calendar for primary and secondary schools is determined by Beijing Municipal Commission of Education, and this decision is made at least one year prior to implementation, and the school calendar for primary schools is the same as that for secondary schools in Beijing. The start and end dates of the winter and summer school holidays can be regarded as repeated exogenous shocks to urban traffic and air pollution conditions. We collect school calendars from 2009 to 2011.¹⁰ We create two dummies: *SH_SUMMER* and *SH_WINTER* indicate whether a day is in the summer or winter school holidays (yes = 1, no = 0), respectively. In this way, we separate all the days in our study period into treatment group (days in school holidays) and control group (days NOT in school holidays). The biggest difference between these two groups is that driving-to-school commuting does not exist in the treatment group.

4.1.2. Traffic congestion index

One key variable in our study is the traffic congestion index (*TCI*). This daily index is calculated by the Beijing Transportation Research Center (under the Beijing Municipal Commission of Transport), as the aggregate measure of motorized traffic speed and road congestion in Beijing's metropolitan area.¹¹ *TCI* has already been standardized, with 0 referring to no congestion at all and 1 referring to complete gridlock. An increase in *TCI* indicates that traffic flow becomes slower and congestion becomes more serious. For the period between January 2009 and April 2011, we can only obtain the daily morning rush-hour *TCI* data only for the workdays (the same dataset as that used in Sun et al. (2014)); for year 2013, we are able to obtain the daily morning and evening *TCI* for workdays,¹² the latter one is used for robustness check.

4.1.3. Air quality: PM_{10} and $PM_{2.5}$

The third set of key variables is collected for air quality. We have two measures of particulate matter concentration. First, we obtain the mean value of the PM_{10} concentration in Beijing's metropolitan area for the period of 2009–2011. This PM_{10}

¹⁰ Source: <http://www.bjedu.gov.cn/publish/portal0/tab153/>.

¹¹ *TCI* is calculated by using real-time speed and location of nearly 40 thousand moving cars weighted according to the traffic volumes of each road (Wen et al., 2014; Anderson et al., 2015). See details on <http://faculty.maxwell.syr.edu/jyinger/classes/PA1735/studentpapers/2014/Dong.pdf>.

¹² Unfortunately, we are unable to obtain the *TCI* data for the period of May 2011 to December 2012.

data is converted from the daily air pollution index (API) released by the Beijing Municipal Environmental Protection Bureau.¹³ Second, we collect the hourly PM_{2.5} concentration data for the same period from the United States Embassy in Beijing (a single monitor), and convert the hourly data to daily mean concentration.¹⁴ Since some environmental studies show some concerns over the quality of Chinese official air pollution data (Ghanem and Zhang, 2014), this PM_{2.5} data by US Embassy is used for robustness checks.

4.1.4. Control variables

Beijing has implemented a “one day per week” driving restriction policy since October 2008. Under this policy, automobiles are not permitted to be on the road on any given workday according to the last digit of their license plates. Each workday has one of the five combinations of restricted numbers—1/6, 2/7, 3/8, 4/9, and 5/0. In China, most people dislike the number “4” because it sounds like “death” in Chinese. Therefore fewer cars have the last digit “4” compared to the other numbers. That means traffic congestion is much worse on workdays when cars having license numbers with a final digit of “4” or “9” are not permitted to be on the road (Sun et al., 2014; Anderson et al., 2015). Therefore, the driving restriction policy provides another repeated exogenous shock to traffic congestion and related air pollution. We use this as an additional instrumental variable in some regressions.¹⁵

We also control for various daily weather conditions, including daily mean temperature (*TEMP*), daily mean humidity (*HUMI*), daily mean wind speed (*WIND*), whether it rains (*RAIN*) or snows (*SNOW*). Such data comes from the [TuTiempo.net](http://www.tutiempo.net) climate database.¹⁶

In the empirical analysis below, we mainly focus on the workdays from January 2009 to April 2011. This is the longest continuous period for which we are able to match congestion and pollution variables. This period covers two summer school holidays and three winter school holidays. Table 1 shows the definitions and summary statistics for all variables.

4.2. Patterns

The spatial separation between schools and households is expected to generate long-distance driving-to-school trips on school days. To provide some intuition, Fig. 2 shows the temporal variation of weekly average *TCI* in our study period.¹⁷ We can clearly see significant drops in *TCI* when school holidays start, indicating much less congestion. During school holidays, almost no students attend primary or secondary schools in Beijing. Two-worker households are quite common in Chinese cities and parents cannot take vacation on school holidays.¹⁸ Some robustness checks are used to rule out the impacts from the absence of drive-to-work trips during the school holidays (see details in Section 5.3). Therefore, the *TCI* declines on school holidays may mainly be attributed to the disappearance of driving-to-school trips. Such repeated drops in morning rush-hour *TCI* inspire us to use school holiday start/end dates as repeated exogenous events to study the impact of driving-to-school trips on traffic congestion. It should be noted that, weekly morning rush-hour *TCI* has a deeper drop around each of the winter school holidays than each of the summer school holidays. The possible reason is that the one-month winter school holiday covers the seven-day Chinese Spring Festival, and many Beijing urbanites go back to their original hometowns or leave the city for tours around this national holiday. Therefore, in the empirical analysis below, although the regression results are reported for both summer and winter school holidays, we rely more on the results for summer school holidays. In a scientific study, Yang et al. (2016) use GPS record of three selected routes and calculate the emission inventories of many pollutants, and their results show significant differences of average speed and air pollution between school days (September–October, 2013) and summer school holidays (July–August, 2013) in Beijing. We will further identify the causal mechanisms behind the patterns discussed above – the “chain” channel from driving-to-school trips to congestion and then to pollution.

4.3. Empirical strategy

We employ the two-stage least squares (2SLS) regression method as our empirical strategy. In the first stage of 2SLS, we regress traffic congestion index on school holiday variable(s) and other control variables. As the driving-to-school trips only exist on school days but disappear in the school holidays, the school calendar is used to investigate the link between driving-to-school and traffic congestion in this stage. The estimation with long time period is to show the different congestion levels between school holidays and non-school-holiday workdays. However, we doubt that seasonality and many unobserved factors (such as gas price, GDP and population) may co-vary with (but are not related to) school holiday schedule, which may bring empirical challenge to identify the pure effect of driving-to-school trips. Therefore, we then restrict the study period to narrow time windows (see Fig. 3), such as 15 days (or even 7 days) on either side of the school holiday start/end dates.

¹³ Andrews (2008) presents the conversion formula. API data source: <http://www.bjepb.gov.cn/>. Beijing's daily API data is not available for the year of 2013.

¹⁴ Some recent studies suggest using two different data sources for robustness checks (Chen et al., 2012). However, the limitation of PM_{2.5} data is that it is collected from a single monitor, and this could also result in estimation bias.

¹⁵ We will present the Sargan over-identification test of all instrument variables in some 2SLS regression results.

¹⁶ Weather data come from <http://www.tutiempo.net/en/Climate/Beijing/545110.htm>.

¹⁷ We convert workday *TCI* to weekly average *TCI* here.

¹⁸ See some related media reports: http://www.chinadaily.com.cn/opinion/2016-08/01/content_26290021.htm; <http://www.globaltimes.cn/content/869051.shtml>. Some parents even have to take their children to the work.

Table 1

Variable definitions and summary statistics.

Variable	Definition	Period	Obs.	Mean	Std. Dev.
<i>TCI</i>	Daily traffic congestion index in morning rush hours	2009–2011.4	554	0.499	0.143
		2013	239	0.493	0.145
<i>TCI_E</i>	Daily traffic congestion index in evening rush hours	2013	239	0.602	0.153
<i>PM10</i>	Daily mean PM ₁₀ concentration (in mg/m ³)	2009–2011	554	0.125	0.081
<i>PM2.5</i>	Daily mean PM _{2.5} concentration (in mg/m ³)	2009–2011	482	0.102	0.077
<i>SH_WINTER</i>	1 = winter school holidays, 0 = otherwise	2009–2011	554	0.081	0.273
<i>SH_SUMMER</i>	1 = summer school holidays, 0 = otherwise	2009–2011	554	0.130	0.337
<i>TEMP</i>	Daily mean temperature (°C)	2009–2011	554	11.303	11.839
<i>HUMI</i>	Daily mean humidity (%)	2009–2011	554	49.545	20.847
<i>WIND</i>	Daily mean wind speed (m/s)	2009–2011	554	11.377	5.771
<i>RAIN</i>	1 = rainy day, 0 = otherwise	2009–2011	554	0.217	0.412
<i>SNOW</i>	1 = snowy day, 0 = otherwise	2009–2011	554	0.025	0.157
<i>NUM49</i>	1 = driving restriction (no driving during the day if plate number ends with 4 or 9), 0 = otherwise	2009–2011	554	0.200	0.401

Note: Some variables have missing values. We drop the daily PM_{2.5} concentration observations with less than 50% valid hourly readings in the 24-h day.

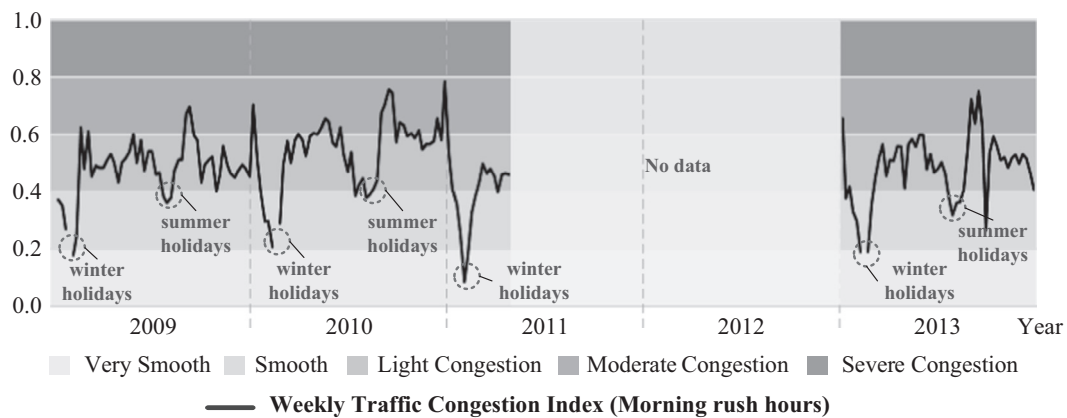


Fig. 2. Weekly traffic congestion index (morning rush hours). Source: Beijing Transportation Research Center.

Unobserved factors tend to keep constant in the narrow time windows.¹⁹ By doing so we can mitigate the noises brought by these factors. We also separate the narrow time windows into those around summer, and those around winter school holidays. Some robustness checks and discussions are provided to confirm our empirical findings in Section 5.3.

In the second stage, we regress the daily PM₁₀ concentration on *TCI* and controls in an air pollution equation. The novel part at this stage is that we link it with the first stage so that we actually run a two-stage regression where school holiday dummies serve as instrumental variables (IVs) for traffic congestion. This allows us to mitigate the endogeneity problem and obtain an accurate estimation of the causal relationship from drive-to-school trips to the increase in PM₁₀ concentration.²⁰ It should be noted that, our instrumental variable strategy is only valid if the school holiday variables pass the “exclusion” test – they should only influence air pollution through the traffic congestion channel (in other words, they should not be correlated with air pollution through any other channel). We justify this in three ways. First, the school calendar is a centralized decision made at least one year before its implementation. Second, the one-month or even two-week time windows help us exclude the omitted variable bias and reduce the possible endogeneity.²¹ Third, we further conduct several robustness checks in Section 5.3 to address the concerns of missing variables and confirm our major findings.

¹⁹ For instance, according to monthly production statistics for Beijing, the month-on-month growth rates of industrial output in July and August are quite comparable to those for other months, with no significant sign of a “slowdown”. Source: <http://www.bjstats.gov.cn/sjfb/bssj/jdsj/2009/>. As the gas price is set by the government (does not vary frequently) in China, the price keeps constant in the narrow time windows.

²⁰ We interviewed some parents of school-aged children, most said they did not want their children to miss school even when the air pollution is worse. They do not worry much about health consequences for their children when their children are at school, the reason is that students are more likely to stay in the classroom on days when the air quality is worse.

²¹ According to Beijing city government’s public information, there are no traffic and environmental policy changes in the narrow time windows.

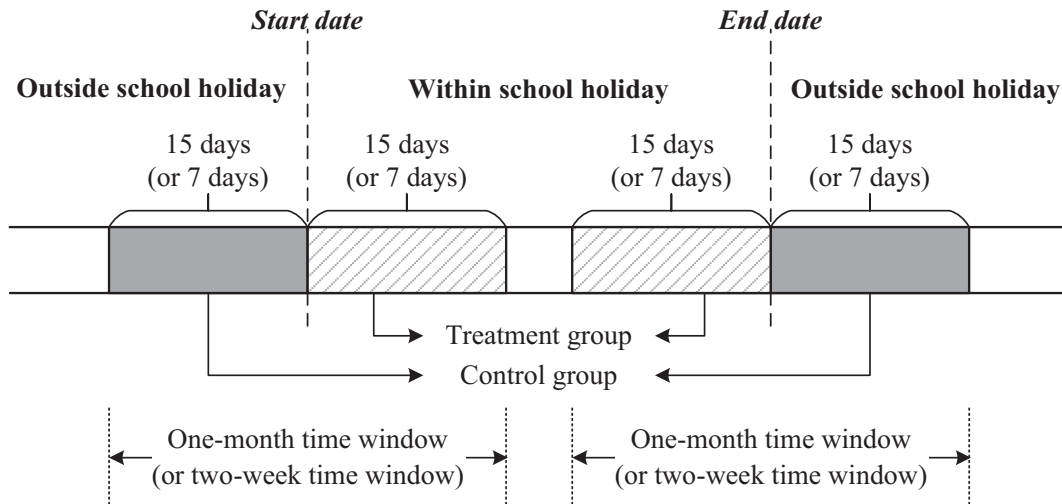


Fig. 3. Narrow time window estimation.

5. Model specification and empirical results

5.1. Model specification

As mentioned above, we employ 2SLS regression to better illustrate the chain of “driving-to-school trips – traffic congestion – air pollution”. The detailed specifications for the first-stage traffic congestion equation and the second-stage air pollution equation are shown in Eqs. (1) and (2), respectively.

1st stage : TCI_t

$$= \alpha_0 + \alpha_1 \cdot SH_WINTER_t + \alpha_2 \cdot SH_SUMMER_t + \alpha_3 \cdot NUM49_t + \alpha_4 \cdot \mathbf{W}_t + \alpha_5 \cdot \mathbf{D}_t + \alpha_5 \cdot \mathbf{Y}_t + f(T) + \varepsilon_t \quad (1)$$

$$\text{2nd stage : } PM10_t \text{ (or } PM2.5_t) = \beta_0 + \beta_1 \cdot TCI_t + \beta_2 \cdot \mathbf{W}_t + \beta_3 \cdot \mathbf{D}_t + \beta_4 \cdot \mathbf{Y}_t + f(T) + \mu_t \quad (2)$$

where the dependent variables are daily traffic congestion index (TCI_t) and air pollution indicators ($PM10_t$ or $PM2.5_t$) on day t , measuring the negative traffic and pollution externalities respectively. Dummy variable SH_WINTER_t or SH_SUMMER_t turns on when the day is during the winter or summer school holiday, respectively. They capture drops in traffic congestion due to the reduction of driving-to-school trips during school holidays. Dummy variable $NUM49_t$ captures the worse congestion on the days with driving restriction of 4/9.

Vector \mathbf{W}_t controls for short-term fluctuations caused by various weather factors. Vector \mathbf{D}_t controls for day-of-week fixed effects on traffic congestion and air pollution. Vector \mathbf{Y}_t of year dummies captures the yearly difference. The polynomial time trend $f(T)$ captures any pre-existing trend in congestion and pollution for a long time period, T is set as a continuous time trend within each year.²² Thus, the holiday dummies may better capture the discontinuity effects of the school holidays. In the regressions of narrow time windows where no continuous time trend is assumed, we do not include either the polynomial time trend or the year fixed effects. The error terms in two stages are denoted by ε_t and μ_t , respectively.

We expect that the coefficient of the school holiday dummy (either α_1 or α_2) in the first-stage equation is significantly negative, it means the long-distance driving-to-school trips indeed impose a burden on aggregate traffic congestion. Conditional on this, if the coefficient of TCI (β_1) in the second-stage equation is significantly positive, we can say that either winter or summer school holiday has an environmental consequence through the channel of removing driving-to-school trips from the road network.

5.2. Empirical results

5.2.1. Empirical results of the traffic congestion equation

We firstly presents the regression results for the first-stage traffic congestion equation, showing the link between driving-to-school and congestion in Table 2. Column (1) reports the regression results for the whole sample (all workdays from January 2009 to April 2011). The 2nd -order polynomial time trend and yearly fixed effects are included. Columns (2) to (4) pre-

²² The first day of the summer school holiday takes the value of 0. For instance, the first day of summer school holidays in 2009 is July 11, so the value of T on this day is 0, and its values on January 1st and December 31st are -191 , and $+173$, respectively. For the year 2010, the first day of the summer school holiday is July 13, so the value of T on this day is 0, and its value on January 1st is -193 . Our estimation results are not influenced by whichever day we set $T = 0$.

sent the regression results with the one-month time window sample (15 days on either side of the school holiday start/end dates), and columns (5) to (7) present the regression results for the two-week time window sample (7 days on either side of the school holiday start/end dates).

Generally, the coefficients of the school holiday dummies are significantly negative, indicating that traffic congestion is significantly reduced during school holidays. For the regressions of the whole sample and one-month sample (columns (1) to (4)), the coefficient of *SH_WINTER* has a larger absolute value than the coefficient of *SH_SUMMER*. This is because the winter school holiday includes the Chinese Spring Festival, as mentioned before. In addition, the 4/9 effect of driving restriction still holds but its coefficient loses significance when the sample size becomes smaller.

Since the omitted variables are more likely to be unchanged in narrower time windows, the two-week time window estimates are more reliable but the sample size becomes much smaller. Columns (5) to (7) reveal that *TCI* in school-holiday workdays is about 0.12 (about 20% of the mean value) lower than that for non-school-holiday workdays.²³ Given the non-linear relationship between traffic flow and speed, when the road network enters congestion status, the increase in the congestion level is often faster than the increase in the number of motor vehicles on the road network. Thus, it seems reasonable that these driving-to-school trips cause about 20% of aggregate congestion in our estimation.

5.2.2. Empirical results of the air quality equation

Table 3 reports the traditional ordinary least squares (OLS) and the two-stage least squares (2SLS) regression results for the air quality equation for the whole sample and the narrow time windows (one-month sample and two-week sample).

In column (1) with OLS estimation, the coefficient of *TCI* is negative but insignificant. This may be due to the endogeneity between traffic congestion and pollution, because on polluting days, people may choose not to drive. We then turn to the 2SLS regressions in the remaining columns. The regression of the traffic congestion equation serves as the first stage, and the instrumental variables include *SH_SUMMER*, *SH_WINTER* and *NUM49*. The first-stage regressions for columns (2) to (5) in this table are reported in columns (1), (3), (4) and (6) in Table 2, respectively. The coefficient of *TCI* in column (2) becomes positive.²⁴ The sign inversion for this *TCI* variable from the OLS to the 2SLS regression may indicate that the endogeneity issue (reverse causality) does exist. We further construct sub-samples which include 15 days on either side of school holiday start/end dates (one-month time window). Columns (3) and (4) cover the narrow time windows of winter holiday and summer holiday, respectively. The coefficient of *TCI* is significantly positive in column (4), but not in column (3). Some other possible channels such as coal-based winter heating and firework displays may affect coefficient significance in the second stage of the winter holiday sample.

We further shrink the sample size in column (5) by only focusing on the 7 days on either side of the summer school holiday start/end dates. For this narrower time window sample, the coefficient of *SH_SUMMER* becomes smaller but still significant. The Sargan statistic shows that the instrument variables pass the test of over-identification. To further examine whether the school holiday alone brings enough exogenous variation to cause traffic congestion and hence to cause the air pollution change, in column (6), we drop the *NUM49* and keep *SH_SUMMER* as our sole IV for the first stage (thus the degree of freedom can increase). Compared with column (5), the coefficient of *TCI* is still significant and the *F* value in the weak IV test also becomes larger. It is acceptable considering such a small sample size of two-week time windows. This means that the summer school holidays generate sufficient exogenous variations in *TCI* to induce the change in *PM₁₀* concentration. The negative coefficient of *TCI* in each of these two columns implies that the reduction in *TCI* observed during summer holidays leads to a significant decrease in *PM₁₀* concentration.²⁵

5.3. Robustness checks

As the first set of robustness checks, we use other time windows outside school holidays as a placebo test. We set two hypothetical one-month “school holidays” – the first one starts on November 1 and ends on November 30, and the second one starts on May 20 and ends on June 20. These two periods are in fact in the middle of the fall and spring semesters. We replace the school holiday dummies in Eq. (2) with *SH_FALL* (1 = within the hypothetical fall school holiday) and *SH_SPRING* (1 = within the hypothetical spring school holiday). Columns (1) to (4) in Table 4 show the regression results for these two-week time window samples (7 days on either side of the hypothetical school holiday start/end dates). The coefficients of *SH_FALL* and *SH_SPRING* are insignificant in columns (1) and (3), indicating that there is no difference in traffic congestion around the start/end dates of the time windows we examine. The second-stage regressions in columns (2) and (4) report insignificant effects of *TCI* on *PM₁₀*.

Another major concern is the reduction of parents' drive-to-work trips may also exist in school holidays. In other words, if parents take vacation and stay with their children during school holidays, we will observe the decline in traffic congestion. As the second set of robustness checks, we compare the variation of morning and evening rush-hour *TCI* around the school

²³ In other words, the average speed of motor vehicle on a typical non-school-holiday workday is 0.76–0.85 of that on a workday in summer school holiday.

²⁴ The regression in column (2) is the only one where the instrument variables do not pass the over-identification test. The instrument variables pass the over-identification test in all the remaining regressions for narrow time windows.

²⁵ To prove the statistical exogeneity of IVs, we predict the residual for each first-stage regression in Table 3, and include the residual as an explanatory variable in the second-stage equation with other controls. The coefficient of this variable is not significant in each regression.

Table 2

Regression results of the traffic congestion equation (the first stage).

Dependent variable: <i>TCI</i>	Whole period	One-month time window			Two-week time window	
	Summer and winter holidays (1)	Summer and winter holidays (2)	Winter holiday (3)	Summer holiday (4)	Winter holiday (5)	Summer holiday (6)
<i>SH_WINTER</i>	−0.213*** (0.0173)	−0.199*** (0.0217)	−0.183*** (0.0219)		−0.0763** (0.0310)	
<i>SH_SUMMER</i>	−0.138*** (0.0151)	−0.148*** (0.0257)		−0.124*** (0.0240)		−0.118*** (0.0355)
<i>NUM49</i>	0.0960*** (0.0103)	0.0686*** (0.0206)	0.0709** (0.0342)	0.0855*** (0.0278)	0.0534 (0.0459)	0.0692 (0.0487)
Constant	0.628*** (0.0386)	0.317*** (0.0510)	0.354*** (0.0588)	1.148*** (0.154)	0.233*** (0.0750)	1.329*** (0.303)
Day-of-week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Weather variables	<i>RAIN, SNOW, TEMP, HUMI, WIND</i>					
Obs.	554	197	110	87	55	40
<i>R</i> ²	0.553	0.585	0.550	0.633	0.590	0.609

Note: Standard errors in parentheses; * $p < 0.10$. One-month time window covers 15 days on either side of the school holiday start/end dates. Two-week month time window covers 7 days on either side of the school holiday start/end dates (see Fig. 3). Day-of-week fixed effects include four weekday dummies (Monday is the default). The 2nd-order polynomial time trend and yearly fixed effects are controlled in column (1).

** $p < 0.05$.

*** $p < 0.01$.

Table 3Regression results of air quality (PM_{10}) equation (the second stage).

Dependent variable: <i>PM10</i>	Whole period		One-month time window		Two-week time window	
	Summer and winter holidays		Winter holiday	Summer holiday	Summer holiday	
	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
<i>TCI</i>	−0.00229 (0.0255)	0.140*** (0.0422)	0.0317 (0.0641)	0.198*** (0.0758)	0.144* (0.0826)	0.159* (0.0923)
Constant	0.0996*** (0.0340)	0.0129 (0.0392)	0.0437 (0.0339)	−0.322** (0.132)	−0.188 (0.167)	−0.215 (0.183)
Day-of-week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Weather variables	<i>RAIN, SNOW, TEMP, HUMI, WIND</i>					
Instrumental variables	–	<i>SH_WINTER, SH_SUMMER, NUM49</i>	<i>SH_WINTER, NUM49</i>	<i>SH_SUMMER, NUM49</i>	<i>SH_SUMMER, NUM49</i>	<i>SH_SUMMER</i>
Weak IV (<i>F</i> -test)	–	108.478	36.934	18.256	6.284	10.200
Sargan statistic	–	16.555	0.076	2.976	0.189	–
Obs.	554	554	110	87	40	40
<i>R</i> ²	0.222	0.177	0.436	0.262	0.405	0.377

Note: Standard errors in parentheses, One-month time window covers 15 days on either side of the school holiday start/end dates. Two-week month time window covers 7 days on either side of the school holiday start/end dates (see Fig. 3). The 2nd-order polynomial time trend and yearly fixed effects are controlled in columns (1) and (2).

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

holiday start/end dates in 2013.²⁶ Given primary and secondary school students always leave school much earlier (around 3–4 PM) before the evening rush hours (around 6–7 PM), this helps us to address the above concern. Columns (1) and (2) in Table 5 show that there is no significant drop in the evening rush-hour *TCI* during summer school holidays, but the drop for winter school holidays is significant. This can also be explained by the fact that people take vacation and go back to their hometown around the Spring Festival, but few people change their commute behaviors (and take vacation) around summer school holidays. To make it more intuitive, we replace the dependent variable with the *TCI* gap between morning and evening rush hours

²⁶ The evening rush-hour *TCI* data is only available for the year of 2013.

Table 4
Placebo tests for 2SLS regressions.

Period Dependent variable	Hypothetical FALL holiday		Hypothetical SPRING holiday	
	<i>TCI</i> (1)	<i>PM10</i> (2)	<i>TCI</i> (3)	<i>PM10</i> (4)
<i>SH_FALL</i>	0.00648 (0.0261)			
<i>SH_SPRING</i>			0.0127 (0.0252)	
<i>TCI</i>		−0.0776 (1.930)		0.517 (1.504)
Constant	0.677*** (0.0942)	0.0832 (1.116)	0.919*** (0.174)	−0.532 (1.484)
Day-of-week fixed effects	Yes	Yes	Yes	Yes
Weather variables	<i>RAIN, SNOW, TEMP, HUMI, WIND</i>			
Instrumental variables	–	<i>SH_FALL</i>	–	<i>SH_SPRING</i>
Obs.	40	40	37	37
<i>R</i> ²	0.639	0.657	0.614	.

Note: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$. NUM49 is controlled in columns (1) and (3) but not reported.

*** $p < 0.01$.

(*ATCI*) in column (3). The coefficient of *SH_SUMMER* shows that *TCI* decreases by 0.12 in summer school holidays, which is consistent with our 2SLS regression result.²⁷ We also use online dining-out data to test if people have less frequent leisure activities and non-commute trips during the summer holidays. The results show that the amounts of dining-out have no significant difference on either side of the school holiday start/end dates. The results are available upon request.

As the third set of robustness checks, we replace the dependent variable in the second stage with *PM2.5* as well as the logarithmic form of *PM10*. The signs of our key variables are the same with those in Table 3, and the significance levels are also similar. These results are available upon request.

Although we exclude most unobserved variables to support the existence of the “chain” channel in our 2SLS regressions for the narrow time windows and above morning-evening comparison to improve the accuracy of our estimates, we acknowledge that some other unobserved variables may not keep constant in our narrow time windows, which will bring possible bias.²⁸ Future research is encouraged to use more disaggregated congestion and pollution data (rather than aggregated city-level data) to more accurately estimate the sizes of those effects and investigate the spatial difference.

6. Conclusion

To ensure their children's bright futures, Chinese parents compete for high-quality education by sending their children to high-quality primary and secondary schools. However, in a Chinese mega-city like Beijing, the historical dependency in the location of schools (especially good schools), the centralized public goods provision and the constrained housing supply in the downtown jointly result in the spatial separation between where people live and where their children attend schools. Without efficient school bus system, this “schools – homes” spatial separation causes the common phenomenon that a large amount of parents choose to drive private cars over a long distance to deliver their children to schools. Our estimates shows that 15% of morning rush-hour trips consist of such driving-to-school trips.

In this paper, school holidays (especially the summer ones) are used as exogenous repeated shocks to first estimate how much such trips affect Beijing's aggregate traffic congestion. We then employ 2SLS approach to examine the causal effect from the congestion to air pollution. Both the narrow time window (one week on either side of the school holiday start/end dates) and instrumental variable strategy are used to exclude most unobserved variables and mitigate the endogeneity bias. The empirical results show that, all else being equal, workdays in school holidays without such driving-to-school trips enjoy a 20% lower morning rush-hour congestion index (*TCI*) than non-school-holiday workdays. Such sharp drop in *TCI* observed during summer school holidays leads to a significant decrease in *PM*₁₀ concentration. Some robustness checks confirm our key findings. We acknowledge that our estimate is constrained by city-level aggregated data and small sample size, and hence can only be regarded as a first attempt to quantify how the spatial separation between schools and households leads to this negative environmental externality through the transportation channel. Future research is encouraged to implement a specific and large-scale survey to show the detailed patterns and distribution of “schools – homes” spatial mismatch

²⁷ Data source: <http://www.dianping.com>.

²⁸ For instance, driving children to school is more or less likely to happen at the very start/end of the semester. Moreover, teachers and administrative staffs are more likely to commute home in evening rush hours rather than morning rush hours, the possible “overlap” effect is largely excluded in morning-evening comparison.

Table 5

Differential impacts on morning and evening rush-hour TCI.

Dependent variable	TCI (1)	TCI_E (2)	$\Delta TCI = TCI - TCI_E$ (3)
SH_WINTER	−0.204*** (0.0286)	−0.136*** (0.0314)	−0.0681* (0.0374)
SH_SUMMER	−0.162*** (0.0213)	−0.0383 (0.0234)	−0.124*** (0.0278)
Constant	0.553*** (0.0486)	0.564*** (0.0535)	−0.0108 (0.0637)
Day-of-week fixed effects	Yes	Yes	Yes
2nd –order polynomial time trend	Yes	Yes	Yes
Other control variables	NUM49, RAIN, SNOW, TEMP, HUMI, WIND		
Obs.	239	239	239
R ²	0.613	0.583	0.616

Note: Standard errors in parentheses; ** $p < 0.05$. The time period covers all workdays in 2013.* $p < 0.10$.*** $p < 0.01$.

within the city. More individual travel behavior data and spatially disaggregate congestion measures are helpful to further investigate the link between school driving and traffic congestion at each location.

Given the above empirical findings, it is expected that reducing the spatial mismatch of good schools and homes will mitigate traffic congestion and air pollution. In recent years, Beijing municipal government has sought many solutions to this “schools – homes” spatial separation problem, such as relocating good schools (or establishing new ones) in suburban areas to match the ongoing residential suburbanization, periodically adjusting the good schools’ corresponding zones, and allowing private-public partnerships in good school provisions and school bus services. Based on potential disaggregate data, future research will yield several important implications to empirically examine the effects of school supply, urban planning and management strategies on congestion and air pollution.

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