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Does subway expansion improve air quality?☆

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ABSTRACT

Major cities in China and many other fast-growing economies are expanding their subway systems in order to address worsening air pollution and traffic congestion. This paper quantifies the impact of subway expansion on air quality by leveraging fine-scale air quality data and the rapid build-out of 14 new subway lines and 252 stations in Beijing from 2008 to 2016. Our main empirical framework examines how the density of the subway network affects air quality across different locations in the city during this period. To address the potential endogenous location of subway stations, we construct an instrument based on historical subway planning, long before air pollution and traffic congestion were of concern. Our analysis shows that an increase in subway density by one standard deviation improves air quality by two percent and the result is robust to a variety of alternative specifications including the distance-based difference-in-differences method. The total discounted health benefit during a 20-year period from reduced mortality and morbidity as a result of 14 new subway lines amounts to $1.0–3.1 billion, or only 1.4–4.4 percent of the total construction and operating cost.

1. Introduction

Traffic congestion and air pollution pose pressing urban challenges in many developing and emerging countries. Based on real-time driving data in 2016, TomTom Traffic Index shows that all but one of the top 20 most congested cities are from developing and emerging economies, and eight of them were located in China. Meanwhile, East and South Asian countries, such as Bangladesh, China, India, and the Persian Gulf experienced the highest level of $PM_{2.5}$ concentration in 2015. Ambient $PM_{2.5}$ is the leading environmental factor for death, accounting for about 4.2 million deaths in 2015, nearly 40 percent of which occurred in China (Global Burden of Disease 2015).

The Beijing municipal government has been investing heavily in transportation infrastructures, such as buses, roads, and subway lines to combat traffic congestion and air pollution in the city. From 2007 to 2015, the government's total investment in transportation infrastructure amounted to over 430 billion Yuan (about USD 67 billion). During this period, Beijing rolled out14

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new subway lines with a total length of 440 km. The city's rapid subway expansion is still ongoing: another 12 subway lines with a total length of nearly 378 km are under construction and scheduled to open before the end of 2020. Similar large-scale expansion of subway systems is taking place in major cities throughout China.

Despite the massive investment in subway infrastructure in Beijing and other major cities in China, rigorous evaluation of the impacts of subway expansion is lacking. This paper investigates the impact of subway expansion on air quality by exploiting the rapid expansion of Beijing's subway system from 2008 to 2016. The expansion of the subway network can create two countervailing forces that could affect air quality. First, the improved subway coverage could lead some commuters to switch from traveling using private cars to using subways (Mohring, 1972). This traffic diversion effect or "Mohring Effect", should relieve traffic congestion and thus reduce air pollution. Second, the improvement in traffic conditions could make driving more attractive and induce additional travel demand using private cars, resulting in a traffic creation effect (Vickrey, 1969; Duranton and Turner, 2011). The net effect of subway expansion on air quality is ultimately an empirical question.

Our empirical analysis leverages rich spatial and temporal variation in air quality and subway coverage across Beijing from 2008 to 2016. The data on air quality come from daily air quality readings from 27 monitors throughout the city. During the data period, 252 new subway stations opened (out of totally 345 subway stations in operation by the end of 2016). The primary empirical strategy examines how air quality across different locations in the city is affected by the changes in the subway network density over time and across space. The main identification concern stems from the potential endogeneity in subway station location choices, in that the locations could be chosen based on the projections of some unobserved factors that could affect future traffic congestion and air pollution. For example, planners might locate subway stations in areas with projected growth in population or travel demand and hence deterioration in air quality. An endogenous location of this sort would lead to an underestimation of the real impact of subway expansion on air quality.

To address this endogeneity concern, we instrument the subway density measure by constructing an alternative density measure based on the historical subway planning map following Baum-Snow (2007). Many of Beijing's subway lines were planned more than 20 years ago, long before traffic congestion and air pollution were of concern. The identification assumption hinges on the fact that these lines were originally designed to facilitate national defense because Beijing, as the Chinese capital, is the home to the country's central government agencies. The subway lines that were originally proposed had similar coverage as the lines that were eventually built. Controlling for a rich set of temporal and spatial fixed effects, the IV results show that a one-standard-deviation increase in the subway density improves air quality by two percent.[1] The estimate implies that the city-wide average reduction in pollution ranges from 0.02 percent from the opening of Line 16 (with a length of 20 km) to 0.24 percent from the opening of Line 6 (with a length of 78 km).

This approach, based on a continuous measure of network density, allows for the spillover effect of subway expansion across the whole network/city, but relies on the assumption that the impact diminishes over distance. To further examine the robustness of our results, we use a distance-based difference-in-difference (DID) method based on the assumption that the impact of subway expansion on air quality is local. We define the locations (of air quality monitors) within 2 km of a subway station as the treatment group and the locations farther than 20 km away from a subway station as the control group. The locations between 2 km and 20 km are used as a buffer zone and are dropped in the analysis to avoid misclassifying the treatment status. Between the treatment and the control group, we focus on changes in air quality 60 days before and after the opening of a subway line. This focus on a shorter time window can better address the concern of unobservables, but it is limited by only being able to examine the short-term impacts.

The key identification assumption of DID is that in the absence of a subway opening, the air quality in the treatment and the control group would follow similar trends. Subway construction could potentially cause ground construction dust and worsen the traffic congestion, leading to an overestimation of the pollution reduction effect. However, this concern is mitigated because Beijing's safety regulations require a three-month trial running period before the opening of a new subway line, thus, physical construction has to end at least three months before the opening of the line (Gu et al., 2018). We use an event study analysis to show the parallel trends hold for pre-opening periods in general. We also show robustness of our findings by restricting the control group to the monitors that are located 20 km farther from the new subway stations but within 2 km distance of subway stations opened in the past and to be opened in the future.

The DID specification shows that subway expansion improves air quality in the vicinity (within 2 km) of the new subway line by 7.7 percent, relative to the area outside of the 20 km radius within the 60-day time window. Allowing the effects to vary over time, we show that the effect becomes the largest around 50–60 days after opening. The DID specification considering heterogeneity in subway density shows that air quality improves further as more new subway stations are opened near a monitoring station.

Our paper adds to the emerging literature on the impact of subway expansion on air quality. Chen and Whalley (2012) estimate the causal effect on air pollution from the opening of one subway line in Taipei based on a regression discontinuity (RD) framework. They find that the opening of the Taipei Metro reduced air pollution from carbon monoxide (CO), one key tailpipe pollutant, by 5–15 percent. Zheng et al. (2017) use the DID method to estimate the impacts of the opening of the first subway line in Changsha, China and find an 18 percent reduction in CO in the areas proximate to subway stations.

[1] Air quality is measured using Air Pollution Index (API) from 2008 to 2012 and Air Quality Index (AQI) from 2013. These indices are translated from the dominant pollutant of the day piece-wise linearly. From 2008 to 2012, the index accounts for sulfur dioxide (SO_2), nitrogen dioxide (NO_2), suspended particulates (PM_{10}). Starting from 2013, the index accounts for SO_2, NO_2, PM_{10}, $PM_{2.5}$ and O_3.

Gendron-Carrier et al. (2018) examine 43 cities across the world that had a new subway system open from 2000 to 2014. Using the satellite data on Aerosol Optical Depth around city centers, the paper estimates that particulate concentrations drop by 4 percent following the opening of a new subway system and that the effect persists for up to eight years. Nevertheless, recent papers by Beaudoin and Lin-Lawell (2016) and Rivers et al. (2017) find no evidence of air quality improvement from the expansion of public transit.

This study leverages fine-scale air pollution data and multiple subway lines within the same city to examines the impact of subway expansion on air quality. Different from the RD or DID frameworks in the literature, we use a continuous density measure to characterize the expansion and employ an IV strategy based on the historical planning for identification in our main analysis. By using the continuous measure of subway network density that varies across locations in the city, our analysis focuses on the marginal impact of subway expansion, rather than the impact of building the first subway line.

Rapid urbanization is a global trend, especially in developing and fast-growing economies, and building subway lines constitutes a common supply-side strategy to address traffic congestion and air pollution from automobile usage. Subway construction requires substantial investment, so it is important to understand the benefits of this investment. Based on our empirical results using subway network density, we conduct a back-of-the-envelope calculation of the benefits of subway expansion through improved health outcomes and reduced traffic congestion. The health benefits include both mortality and morbidity impacts, while the benefit from traffic congestion relief stems from the value of reduced travel time of commuters. Our conservative analysis shows that the subway expansion observed during our sample period can provide a total discounted health benefit of \$0.6–2.0 billion during a 10-year period and \$1.0–3.1 billion during a 20-year period, accounting for only 1.1–3.6 percent and 1.4–4.4 percent of the total upfront construction cost and the total discounted operating cost during the same period. Our estimates suggest that although there does exist non-trivial health benefits from improved air quality, the benefit from the reduction of traffic congestion estimated from the literature is more than one order of magnitude larger.

We organize the remainder of the paper as follows. Section 2 discusses the background and related data sets. In Section 3, we describe the empirical strategy. In Section 4, we discuss the estimation results and policy implications. Section 5 concludes.

2. Background and data

In this section, we discuss the challenges of air pollution and the rapid expansion of the Beijing subway system. We then present the main datasets.

2.1. Air quality in Beijing

During the past several decades, China has experienced unprecedented economic growth. From 1980 to 2016, the country's per capita GDP increased significantly, from less than \$200 to over \$8000 in nominal terms according to the World Bank national accounts data. Meanwhile, air quality in major cities such as Beijing is deteriorating. Fig. 1 shows daily and annual $PM_{2.5}$ concentrations in Beijing from 2008 to 2017. The average level is about twice as high as the Chinese annual standard, and six to ten times the U.S. standard.[2]

A rich economic literature has shown robust evidence of the adverse impact of outdoor air pollution on premature mortality and contemporaneous adult health (Chay and Greenstone, 2003; Currie and Neidell, 2005; Greenstone and Hanna, 2014; Lelieveld et al., 2015; Schlenker and Walker, 2015; He et al., 2016). The epidemiology literature has linked chronic obstructive pulmonary disease (COPD), ischemic heart disease (IHD), and lung cancer (LC) to $PM_{2.5}$ (Burnett et al., 2014). According to the Global Burden of Diseases (Cohen et al., 2017), outdoor air pollution contributed to 4.2 million premature deaths in the world in 2015; 40 percent of those occurred in China.

The major sources of outdoor air pollution such as $PM_{2.5}$ include power plants, automobiles, and industrial activities. The relative contribution of each source varies across locations. Quantifying the contribution of urban traffic to $PM_{2.5}$ is challenging because tailpipe emissions lead to secondary $PM_{2.5}$, whereby motor-vehicle emissions are transformed into ambient air pollution through complicated chemical processes. In practice, air quality modeling has yielded a wide range of results. In U.S. cities, the contribution of motor-vehicles to air pollution ranges from 5 percent in Pittsburgh, PA to 55 percent in Los Angeles, CA (Tager et al., 2010). Zhang et al. (2013) estimate the contribution of traffic and waste incineration to air pollution to be 4 percent while Lelieveld et al. (2015) find that motor-vehicle travel alone contributes 3 percent of air pollution in Beijing. However, due to different definitions of the toxic level of each pollutant (such as $PM_{2.5}$, NO, SO_2 and O_3), the level of air pollution from ground traffic remains uncertain.

2.2. Beijing subway expansion

During the past two decades, the Chinese automobile industry has grown to be by far the largest in the world, with a total output of around 29 million units including 24.8 million passenger vehicles, in 2017. Private vehicle ownership in China was

[2] The U.S. Environmental Protection Agency (EPA) sets the U.S. standard as 12 $\mu g/m^3$ annually and 35 $\mu g/m^3$ daily while the China Ministry of Environmental Protection (MEP) sets the Chinese standard as 35 $\mu g/m^3$ annually and 75 $\mu g/m^3$ daily.

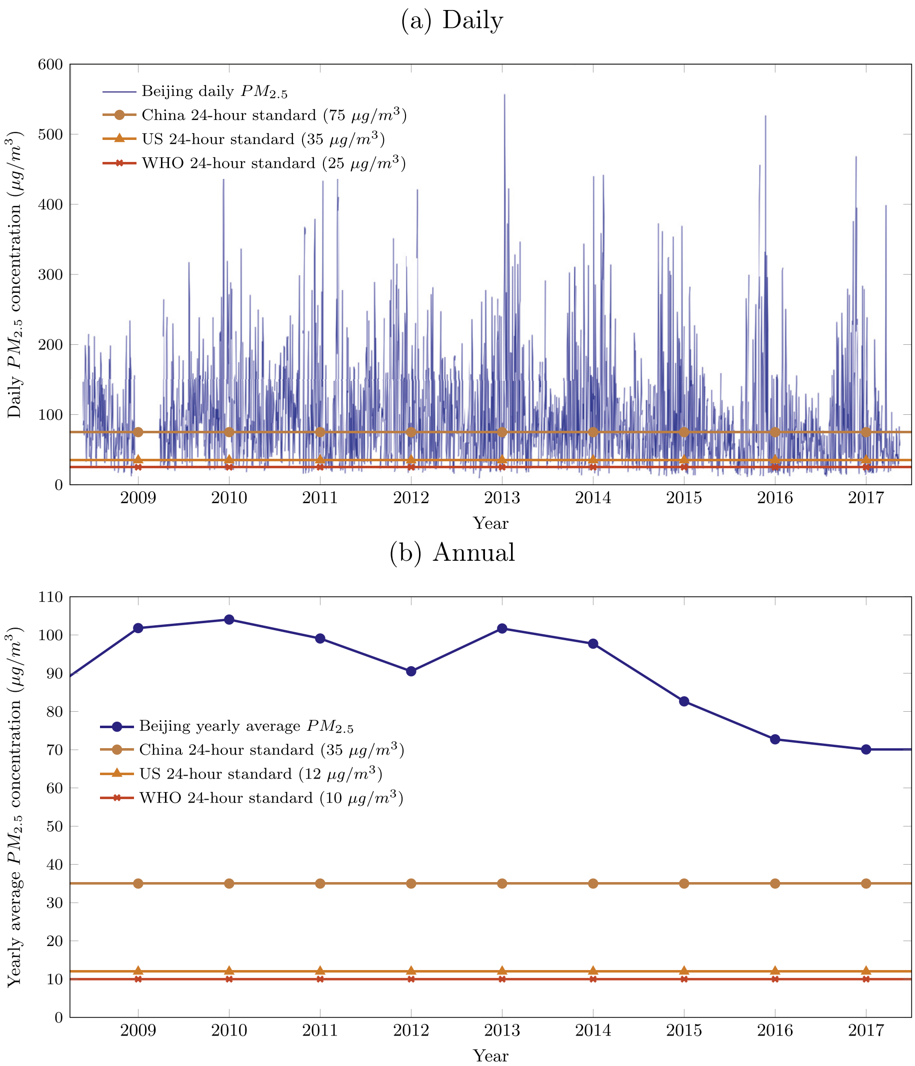

Fig. 1. Beijing $PM_{2.5}$ concentration ($\mu g/m^3$).

uncommon before 2000 but the sales of new passenger vehicles in China increased dramatically after the turn of the century, growing from less than one million units in 2001 to nearly 25 million in 2017 and surpassing the U.S. market in 2009. Beijing has led the way in vehicle ownership growth, transitioning from a city on bikes to a city in cars during this period: Beijing's stock of passenger vehicles increased from about 1.1 million units in 2001 to nearly six million units in 2018. Beijing is now routinely ranked as one of the most congested cities in the world, with the average traffic speed during peak travel times often less than 15 miles per hour.

The Beijing municipal government has taken several measures in order to control the air pollution and the traffic congestion caused by the city's increasing vehicle ownership. One measure is the driving restriction policy started in 2008 whereby vehicles are banned from driving one day per week based on the last digit of the license plate. During important events such as the 2008 Olympic Games or when the air pollution is extremely hazardous (e.g., during the "red alert" days), half of all private vehicles are restricted from the road (with the restriction based on odd and even numbers).[3] Viard (2015) find that traffic restriction in Beijing led to a 19 percent decline of API during every-other-day restrictions and a seven percent decline during one-day-per-week restrictions. This is consistent with the findings of Chen and Jin (2013), who examine the effectiveness of different environment measures that the Chinese government adopted to prepare for the 2008 Olympic Games.

[3] The Emergency Management Division from the Beijing Environmental Protection Bureau issues air pollution alerts based on the four-tiered pollution warning system. *Blue*: AQI > 200 for one or more days; *Yellow*: AQI > 200 for 2 or more days; *Orange*: AQI > 200 for 3 or more days and AQI > 300 for 2 consecutive days; *Red*: AQI > 200 for 4 or more days and AQI > 300 for 2 consecutive days or AQI > 500 for any 24-h period.

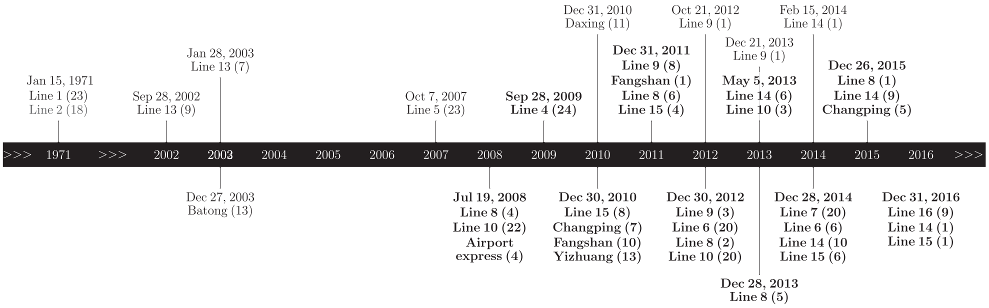

Fig. 2. Beijing subway expansion timeline.

Table 1
Variable descriptions.

Variable	Definition
(a) Air Pollution Indicators, monitoring station $(i) \times$ daily (t)	
API_{it}	Air Pollution Index ranging from 0 to 500. This index measured between 2008 and 2012 and it accounts for sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and suspended particulates (PM_{10}).
AQI_{it}	Air Quality Index ranging from 0 to 500. This index has been measured since 2013 and it accounts for SO_2, NO_2, PM_{10}, $PM_{2.5}$ and O_3.
(b) Subway Density Measures, monitoring station $(i) \times$ daily (t)	
$Density_{it}$	Subway network density centered at monitoring station *i*, which is defined as the total number of stations at time *t* weighted by the inverse of squared distances from monitoring station *i* to each subway station in Beijing.
$\widetilde{Density}_{it}$	Subway network density centered at monitoring station *i*, which is defined as the total number of stations at time *t* weighted by both the daily ridership of each subway line and the inverse of squared distances from monitoring station *i* to each subway station in Beijing.
$Treated_{it}$	Treated group or treated air pollution monitoring station. 1 if it is treated, 0 otherwise. Air pollution monitoring station *i* is treated when there is at least one new subway station (*j*) opened within 2 km distance. $N_{it} = \mathbf{1}(Post_t) \times \sum_{j \in N_t} \mathbf{1}(Distance_{ij} \leq 2km)$
(c) Weather Variables, daily (t)	
Air temperature (^oC)	Average daily temperature.
Relative humidity (%)	Average daily relative humidity.
Precipitation (mm)	Total daily rainfall or snowmelt.
Wind speed (km/h)	Average daily wind speed.
Wind direction (cat.)	The vector summation of hourly wind direction with its speed as the length of each vector.
Rain/Snow/Storm/Fog	Rain/Snow/Storm/Fog dummy: 1 if there was rain/snow/storm/fog, 0 otherwise.

Driving restriction policy, on the other hand, may have incentivized households to buy a second vehicle in order to bypass the driving restrictions.[4] In an additional attempt to curb the growth in vehicle ownership, the Beijing municipal government adopted a quota system for new vehicles in 2012 by capping the monthly number of new vehicle sales. In addition, a limited number of vehicle licenses is allocated through a lottery system (Li, 2018). The winning odds of the license plate lottery in Beijing have decreased from 1:10 in early 2012 to nearly 1:2000 in 2018 as the pool of lottery participants increases dramatically and the cap tightens over time.

Along with demand-side strategies to reduce traffic, the Beijing municipal government has also been investing heavily in transportation infrastructure such as buses, roads, and subway lines. From 2008 to 2016, 13 new subway lines and one airport expressway were constructed with a total length of 440 km, making the Beijing subway system not only the most rapidly expanded but also the longest in the world.[5] Fig. 2 shows the detailed timeline of Beijing subway expansion, which is still ongoing; another 12 subway lines are under construction and scheduled to open before the end of 2020 with a total length of nearly 378 km. Many other cities in China are also rapidly expanding their subway systems.

[4] Davis (2008) studies the effectiveness of driving restriction in Mexico City and finds that the driving restriction leads to worse air quality because more households buy a second vehicle (which tends to be old and release higher pollution). Zhang et al. (2017) find similar results for the driving restriction policies implemented in Bogota, Colombia.

[5] Other four subway systems in the top five worldwide by length (2012): (i) the Shanghai subway is opened in 1995, with a total network length of 423 km; (ii) the London subway is opened in 1863, with a total length of 402 km; (iii) the New York City subway is first opened on Oct 1904 with a total length of 368 km; and (iv) the Seoul subway is first opened in 1974, with a total length of 368 km.

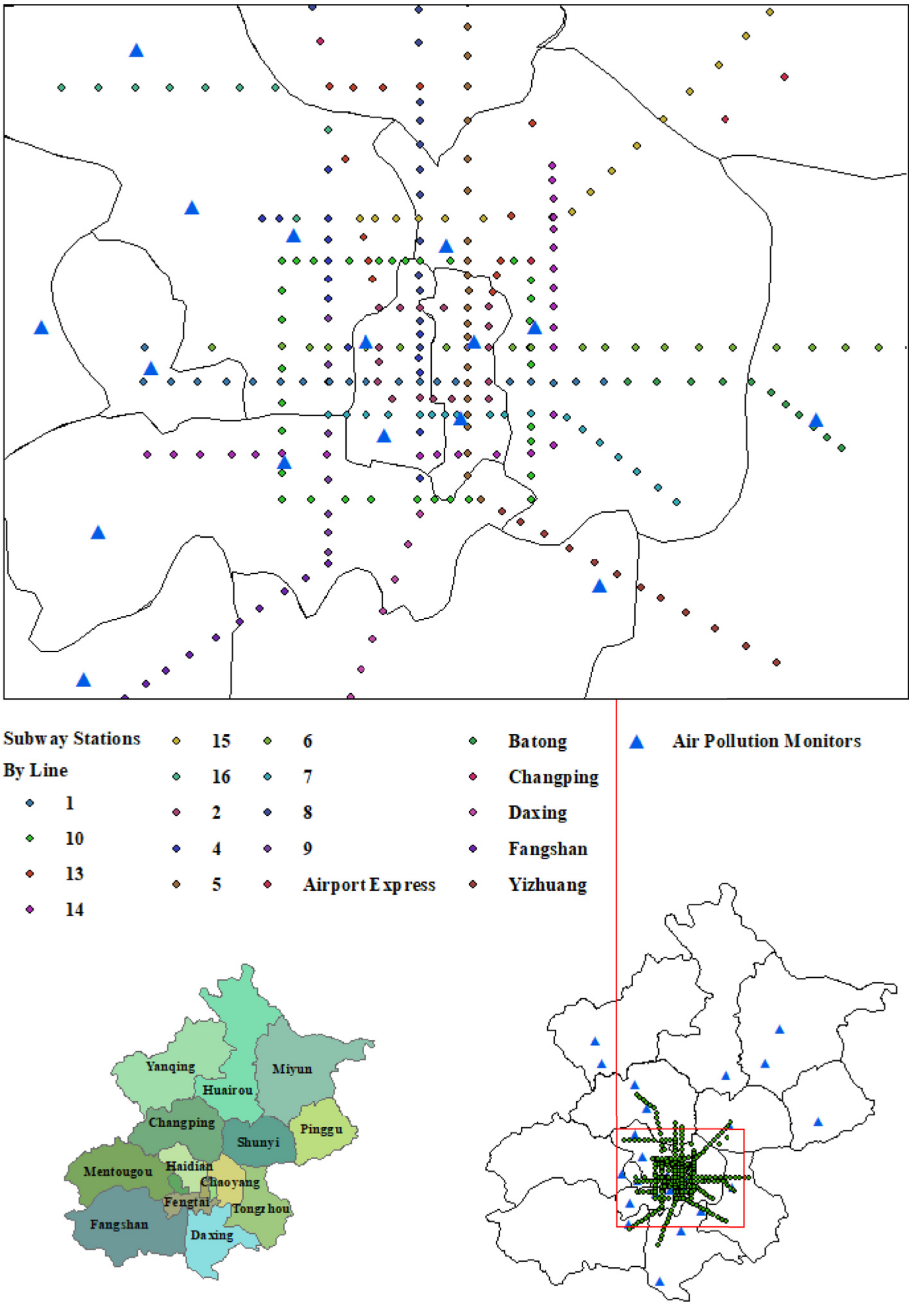

Fig. 3. Air quality monitors and subway stations.
Source: www.bjstats.gov.cn/xwgb/tjgb/ndgb/201402/t20140213_267744.htm

2.3. Data description

Table 1 describes the main variables of our analysis and they are constructed based on three major datasets. The first dataset contains daily air quality readings from all of the 27 monitors in Beijing. Fig. 3 shows the spatial distribution of the 27 air quality monitors; 11 of these are operated by the central government, and the rest are operated by the local government. Geographically, eight monitors lie within the 5th ring road, and the rest are outside the 5th ring road. Air pollution (*Air Pollution*) in Beijing is measured by two different indices: Air Pollution Index (API), available from January 1, 2008 to December 31, 2012, and Air Quality Index (AQI), available from January 1, 2013 to May 12, 2017. Both indices are measured at the monitoring station level on a daily basis. The API is based on three atmospheric pollutants, sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and suspended particulates (PM_{10}). In 2013, the Chinese government replaced API with AQI which considers $PM_{2.5}$ separately from PM_{10}, and

Table 2
Conversion from pollutants concentration to API and AQI.

Air Pollution Index (API)		Pollutants					
value	level	PM_{10} ($\mu g/m^3$)	$PM_{2.5}$ ($\mu g/m^3$)	O_3 ($\mu g/m^3$)	CO (mg/m^3)	NO_2 ($\mu g/m^3$)	SO_2 ($\mu g/m^3$)
0–50	Excellent	0–50				0–80	0–50
50–100	Good	50–150				80–120	50–150
100–200	Slightly polluted	150–350				120–280	150–800
200–300	Moderately polluted	350–420				280–565	800–1600
300–400	Severely polluted	420–500				565–750	1600–2100
400–500	Severely polluted	500–600				750–940	2100–2620
Air Quality Index (AQI)		**Pollutants**					
value	level	PM_{10} ($\mu g/m^3$)	$PM_{2.5}$ ($\mu g/m^3$)	O_3 ($\mu g/m^3$)	CO (mg/m^3)	NO_2 ($\mu g/m^3$)	SO_2 ($\mu g/m^3$)
0–50	Good	0–50	0–35	0–100	0–2	0–40	0–50
50–100	Moderate	50–150	35–75	100–160	2–4	40–80	50–150
101–150	Unhealthy for SG	150–250	75–115	160–215	4–14	80–180	150–475
151–200	Unhealthy	250–350	115–150	215–265	14–24	180–280	475–800
201–300	Very unhealthy	350–420	150–250	265–800	24–36	280–565	800–1600
>300	Hazardous	>420	>250	>800	>36	>565	2100–2620

Note: During 2008–2012, the Chinese government adopts the Air Pollution Index (API) which takes into account three pollutants. Starting from 2013, the Chinese government replaces API with Air Quality Index (AQI) which considers $PM_{2.5}$ separately from PM_{10} as a major pollutant, and also Ozone.

includes ozone (O_3) and carbon monoxide (CO) as major pollutants. The API or AQI for a given day is calculated based on the level of the dominant pollutant during that day and the dominant pollutant is determined by a scoring system as shown in Table 2.[6]

The second dataset records the opening dates and the locations of subway lines. During the data period from 2008 to 2016, 13 new subway lines and one airport expressway with 252 new subway stations were opened. Fig. 3 overlays air quality monitors with subway stations in Beijing as of 2016. Most of the subway stations are located in the central city.[7] Subway stations on the same line could be opened at different dates. For example, some subway stations on Line 8 were opened on the same day as Line 9. Our analysis is thus based on ten major opening dates during the sample period (Fig. 2).[8] Table 3 presents the opening dates of new subway lines with the lines' total length and number of new stations, as well as average measures of the subway density at the locations of air pollution monitoring stations, for each of the ten opening dates. The average standardized network density at the monitoring stations increases from 0.27 in 2008 to 0.96 in 2016. The construction of the subway network density is discussed in detail in the following section.

The third dataset contains daily weather variables: average temperature, average relative humidity, precipitation, and binary variables indicating rain, snow, storm, and fog. It also includes hourly wind direction (measured in degrees from 0° to 359°) and speed. Wind plays an important role in air pollution because it affects the movements of the fine particulates. Since our unit of observation is daily, we need to convert hourly wind speed and direction to the daily level. We calculate the daily wind direction and speed based on the vector summation of hourly wind direction and speed.[9] We then categorize the daily wind directions into 16 groups. Table 4 presents summary statistics for the main daily weather variables and the daily wind directions.[10]

Table 5 presents the sample averages of ln(*Air Pollution*) 60 days before and after the opening of each new subway line. The top panel shows the simple averages, while the bottom panel presents the average residuals after controlling for weather conditions and a rich set of time and location fixed effects (the same set of controls to be used in the regression analysis). The treatment group is defined as the monitoring stations within 2 km of a new subway line, while the control group is defined as the monitoring stations more than 20 km away from the new subway line. The top panel shows a 4 percent increase in air pollution level on average after the opening of a subway line. This counterintuitive result could be driven by seasonality: nine out of the 14 new lines were opened in December and air quality tends to be worse in January and February than in November and December

[6] An alternative air quality measure is the Aerosol Optical Depth (AOD) data from satellites (Gendron-Carrier et al., 2018; Zou, 2018). We do not use the AOD data due to the large number of missing observations caused by the cloud coverage at the daily level.

[7] On December 30, 2010, four subway lines (Line Daxing, Changping, Fangshan and Yizhuang) opened, targeting the suburban districts.

[8] The ten major opening dates are Jul 19, 2008; Sep 28, 2009; Dec 30, 2010; Dec 31, 2011; Dec 30, 2012; May 5, 2013; Dec 28, 2013; Dec 28, 2014; Dec 26, 2015; and Dec 31, 2016. The opening dates within 60 days apart from these major opening are combined with the closest major opening date.

[9] For example, wind at 8:00 a.m. is 30° (angle from North) with wind speed 4 mph; wind at 9:00 a.m. is 90° (E) with a speed 4 mph. The summation of the two wind vectors would be a 60° wind vector with a speed 7 mph.

[10] One may consider a simple average of the hourly wind direction indicators for a day, but this measurement could neglect the magnitude of wind speed and thus bias its impact. Wind directions at the subway station level can help us assess the subway expansion's impact at a particular monitoring station precisely. This approach will be practically feasible to implement as the satellite data (such as Aerosol Optical Depth data) and smart phones (or cards) data are becoming more available.

Table 3
Beijing subway expansion and network density.

Opening	Subway		N. of Stations		Standardized Density	
date (τ)	line (ℓ)	length (km)	new (N_τ)	total ($\mathcal{N}_\tau$)	non-weighted ($Density_\tau/\sigma$)	ridership-weighted ($\widetilde{Density}_\tau/\widetilde{\sigma}$)
Before 2008	1, 2, 5, 13, BT	140	93	93	0.27	0.27
July 19, 2008	8, 10, AE	57	30	123	0.39	0.44
Sep 28, 2009	4	28	24	147	0.45	0.52
Dec 30, 2010	15, DX, CP, FS, YZ	108	49	196	0.57	0.54
Dec 31, 2011	9	36	19	215	0.62	0.56
Dec 30, 2012	6	70	46	261	0.80	0.75
May 5, 2013	14 (West)	14	9	270	0.82	0.76
Dec 28, 2013	8 (Extension)	7	7	277	0.84	0.77
Dec 28, 2014	7	62	42	319	0.93	0.81
Dec 26, 2015	14 (East)	11	15	334	0.94	0.82
Dec 31, 2016	16	20	11	345	0.96	0.82

Note: The names of suburban subway lines are shown as abbreviation: Airport Express (AE), Batong (BT), Daxing (DX), Changping (CP), Fangshan (FS) and Yizhuang (YZ). There were 93 subway stations operating before our data period. Network density centered at an air pollution monitoring station is defined as the weighted sum of subway weighted by the squared inverse distance from the monitoring station to each subway station operating in the network as of the opening date. It is standardized by dividing its standard deviation. The ridership-weighted density is the reweight of the density by ridership of subway line. Standard deviations of the two densities are $\sigma = 3.58$ and $\widetilde{\sigma} = 29.77$ respectively. All density measures are averaged across monitoring stations for each opening date.

Table 4
Summary statistics.

Main variables	Mean	S.D.	Min	Max	N
(a) Air Pollution					
API_{it}	82.84	48.56	5.00	500.00	49103
AQI_{it}	124.64	80.02	8.00	500.00	54939
(b) Subway Density					
$Density_{it}$ (non-weighted)	2.48	3.58	0.01	16.26	297
$\widetilde{Density}_{it}$ (ridership-weighted)	0.19	0.30	0.00	1.34	297
(c) Weather variables					
Air temperature (°C)	12.97	11.39	−15.04	33.05	3533
Wind speed (m/s)	1.97	1.58	0.02	10.21	3533
Precipitation (mm)	1.97	8.82	0.00	262.64	3339
Relative humidity (%)	54.64	20.20	6.97	97.83	3533
Wind direction ($cat.$)	7.95	4.94	1.00	16.00	3533

Note: The air quality panel summarizes the daily Air Pollution Index from 2008 to 2012 and Air Quality Index since 2013 from 27 air quality monitors in Beijing. The density panel summarizes the daily subway density measures at the monitoring station level. The weather panel summarizes the daily, city-level weather conditions.

due to winter heating. The bottom panel shows that after partialling out time and location fixed effects and weather conditions, the opening of a new subway line is associated with a 4.6 percent reduction in air pollution level on average.

Fig. 4 depicts average residuals of ln(*Air Pollution*) from 60 days before to 60 days after the opening of each new subway line for the treatment group and the control group, after partialling out weather conditions and a rich set of time and location fixed effects. The treatment group appears to have a higher air pollution level than the control group (relative to their baseline levels) one month before the opening of the new lines but have a lower level of air pollution about 20 days after the opening. The difference between the two groups seems to increase over time after the opening with the treatment group exhibiting a lower level of air pollution.

2.4. Subway network density

The key explanatory variable in our main empirical specification is an inverse distance-weighted subway density:

$$Density_{it} = \sum_{j \in \mathcal{N}_t} \frac{1}{Distance_{ij}^2},$$

where i, j, and t index air pollution monitoring stations, subway stations, and days, respectively. $\mathcal{N}_t$ is the set of existing subway stations at time t. The subway network density for monitoring station i at time t is the weighted number of subway stations at time t, in which the weight is the inverse of squared distance from the monitor to a corresponding subway station in operation at time t. Following the density measure commonly adopted in the urban literature (Ewing and Cervero, 2010),

Table 5
Changes in air pollution before and after openings.

	ln(*Air Pollution*)			
Control	Before	After	Diff.	Diff-in-Diff.
	4.428	4.437	0.009	
	(0.008)	(0.008)	(0.011)	
Treated	4.483	4.535	0.052	0.043
	(0.018)	(0.022)	(0.028)	(0.031)
	Residualized ln(*Air Pollution*)			
Control	Before	After	Diff.	Diff-in-Diff.
	0.005	−0.004	−0.009	
	(0.005)	(0.005)	(0.007)	
Treated	0.022	−0.033	−0.055	−0.046
	(0.014)	(0.015)	(0.021)	(0.022)

Note: The top panel shows the sample mean of ln(*Air Pollution*) 60 days before and after the opening of each subway line. The bottom panel shows the sample means of residualized ln(*Air Pollution*) after controlling for weather conditions, monitor fixed effects, time fixed effects (year, season, day of week and holiday), and monitor-specific time trends. The treatment group is defined as the monitoring stations within 2 km of a new subway line while the control group is defined as the monitoring stations more than 20 km away from the new subway line. The standard errors are in parentheses.

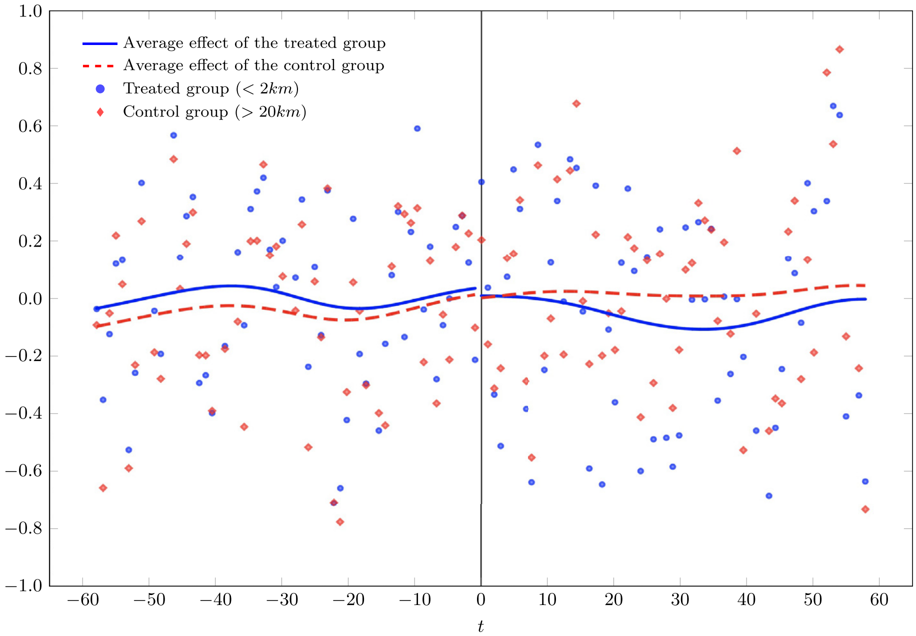

Fig. 4. Residualized ln(*Air Pollution*) for 60 Days Before and After the Opening.

this measure can be considered as the number of subway stations per unit area centered around a given monitoring station. The density measure increases with the number of subway lines. However, a new subway line will change the density measure differently across monitoring stations. The density will increase more for the monitoring stations closer to the subway line.

This subway density measure, however, does not account for the heterogeneity across subway stations or subway lines in their contribution to the whole subway system. For example, major transfer stations that connect multiple subway lines or subway lines in the center of the system play more important roles in the connectivity of the system. To capture this heterogeneity, we generate an alternative density measure which takes into account the ridership of each subway line for robustness checks.[11] The following equation shows the ridership-weighted subway density measure ($\widetilde{Density}_{it}$):

[11] The ridership information at the subway station level would be ideal to be used as a weight. Unfortunately, we could not find such data set at this point. To proxy the ridership at the station level, we use ridership data at the subway line level, treating that each station in a certain subway line has the same ridership.

$$\widetilde{Density}_{it} = \sum_{j \in \mathcal{N}_t} \frac{Weight_{j\ell}}{Distance_{ij}^2},$$

where $Weight_{j\ell}$ denotes the weight of subway station j on subway line ℓ, which equals the ridership share of line ℓ among all subway lines in operation at time t.

Table 3 reports the number of new stations at each opening and the average standardized density in the vicinity of air quality monitors at each opening.

3. Empirical strategy

In this section, we discuss our empirical methods and the identification challenges. The main empirical framework employs subway network density as the key explanatory variable and uses the instrumental variable (IV) approach to address endogenous subway locations. We then present the difference-in-difference (DID) framework as an alternative strategy and discuss analysis of heterogenous treatment effects.

3.1. Network density and air quality

We estimate the following equation:

$$\begin{aligned} \ln(Air\,Pollution_{it}) = \beta_1(Density_{it}/\sigma) + Monitor_i + Trend_{it} + Weather_t\boldsymbol{\beta_2} \\ + Monitor_i \times Driving_t + Year_t + Season_t + DoW_t + Holiday_t + \varepsilon_{it}. \end{aligned} \tag{1}$$

The outcome variable, $\ln(Air\,Pollution_{it})$, is the logarithm of daily Air Pollution Index (API) during 2008–2012 and Air Quality Index (AQI) from 2013 onward. $i = 1, \ldots, 27$ is the index for monitoring stations and $t \in$ [Jan1, 2008, Dec31, 2017] is the index for day. The key explanatory variable is the standardized subway network density, which is defined as $Density_{it}$ divided by its standard deviation, σ. $Weather_t$ is a vector of weather variables including average temperature (C°), relative humidity (%), wind speed (m/s), precipitation (mm), dummies for rain, snow, storm, and fog, and 16 wind direction dummies.

We include monitor fixed effects ($Monitor_i$) to control for unobserved location attributes that affect air quality. We also control for a set of temporal fixed effects including year fixed effects ($Year_t$), season fixed effects ($Season_t$), day of week fixed effects (DoW_t) and holiday fixed effects ($Holiday_t$). To control for other confounding factors that may vary across time but are not adequately controlled by the time fixed effects, we include a monitor-specific time trend, $Trend_{it}$, to allow the unobserved time trend to vary across monitors.[12] We also interact monitor fixed effects with driving restriction policy ($Driving_t$) to allow the effects of driving restrictions to vary by locations. Beijing's driving restriction policy bans some vehicles from driving on a given workday depending on the last digit of the license plate number. This policy follows a pre-set rotation schedule in terms of which pair of numbers (1 and 6, 2 and 7, 3 and 8, 4 and 9, or 5 and 0) is restricted on a given day, and it is not adjusted based on traffic conditions. Because the last digits of license plates are not evenly distributed and this policy thus changes the traffic conditions on the road (Yang and Li, 2017), we construct $Driving_t$ as a vector of five dummies indicating the five pairs of the last digits of license plates. ε_{it} is the random error term.

The key identification challenge is the potential endogeneity of the density variable resulting from non-random placement of subway stations. City planners may place the subway lines and stations in anticipation of the future growth (e.g., population or commercial activities) of different parts of the city, which could have implications for the traffic congestion level. If the subway lines are more likely to be placed in areas with higher anticipated growth of economic activities (hence congestion), the framework using the network density as the key explanatory variable may underestimate the impact of subway expansion on air quality improvement.

To address the concern of non-random placement of subway stations, we use the historically planned subway network to construct an instrument for the density measure, following Baum-Snow (2007), which uses historical highway plans in the U.S. to instrument for observed highway routes. We obtain historical subway plans in 1957, 1983, 1999 and 2003, as shown in Fig. 6. We use the 2003 plan to construct the instrument because it has the most lines and because many of the lines appear in earlier plans. The 1957 plan is the first known plan and provides the basis for the subsequent plans while the 1983 plan defines the "Horizontal + Vertical + Ring" framework of the Beijing subway system, which continues to be used. Because we do not observe the planned opening dates from the historical plans, we assign the actual opening dates to the planned lines. In order to introduce another layer of randomness, we also implement random opening dates within a window of the observed opening date as a robustness check.[13]

The exogeneity assumption of the IV hinges on the fact that the original subway plans were designed to facilitate national defense, with little or no regard for future travel demand or air quality. Many of the lines were planned several decades before

[12] $Trend_{it}$ is a vector of monitor-specific linear time trends (the interaction of the dummy for monitor i and the linear time trend t).

[13] Following Faber (2014), we construct an alternative IV in the earlier version where we use the minimum spanning tree (MST) method to construct hypothetical subway lines with the origin and destination given by the historical subway plans. We straighten up all the historical subway lines and reallocate the observed subway stations to the nearest location on the hypothetical lines. We find similar results using the two different sets of IV.

the construction, long before air pollution and traffic congestion became a concern. During the first planning period of the subway system about 60 years ago, the population in Beijing was less than 3 million, with only 5000 vehicles. Building a subway system requires huge investments and advanced technologies. The then-premier, Zhou Enlai, said, "Beijing is building the subway purely for defense reasons. If it was for transport, purchasing 200 buses would solve the problem."[14]

Beijing's vehicle stock was only 1.5 million in 2003, compared to nearly 6 million by 2018. The rapid increase in vehicle ownership after 2003 was unlikely to be predicted by policymakers and the historical plan is thus unlikely to be correlated with the spatial pattern of traffic congestion and air pollution within the city. The IV is correlated with the density measure because the constructed subway lines largely follow the historical plans, which contain a similar number of transferring stations and level of connectivity as the current subway system.

The empirical approach based on subway network density relies on the spatial and temporal variation of the network expansion. The subway density measure is not a city-wide measure but is local in nature. A new subway line would increase the density more for nearby monitoring stations than for those farther away from the line. The underlying assumption is that the impact of subway expansion on air quality is not uniform across the city but diminishes over distance. With this assumption, this approach allows for system-wide impact or the spatial spillover effect of subway expansion on air quality.

3.2. Difference-in-difference specification

As an alternative specification, we use the DID method which assumes the impact of subway expansion to be confined locally. This assumption allows us to define treatment and control groups. While this assumption may appear to be ad hoc, the advantage of the DID approach is that it can be easily adapted to examine the potential heterogeneity in impacts (e.g., the dynamic impact over time).

Our DID strategy compares the air quality 60 days before and 60 days after each of the 10 opening dates of subway stations between the treatment and the control group. Since the subway lines are designed to serve different areas of Beijing, the set of treated and control monitors vary across different opening dates. We choose the time windows to be 60 days before and after the opening dates to avoid the overlap between the pre-opening and post-opening periods of two consecutive lines. In DID regressions, we restrict our sample to the observations that fall in the 120-day windows around the opening dates.

We define the treatment group as the monitoring stations within 2 km of a subway station and the control group the monitoring stations farther than 20 km of a subway station. We treat the area in between as the buffer zone and drop the monitors in the buffer zone in the DID analysis to address the concern of misclassifying treatment status.

The choice of the treatment group is based on the radius of the impact on commuters' mode of travel to subway stations. The typical length of time that commuters take to travel to subway stations is between 5 and 15 min. Walking and biking are the two most common commuting modes to subway stations in Beijing. The typical walking distance is about 1 km (or 12 min based on a walking speed of 5 km/h) while the typical biking distance is about 3 km. We choose the average of the two as the radius of impact to define the treatment group.[15]

As the subway system is a network, the impact of the opening of a new subway station on air quality could go beyond 2 km. The DID provides estimates of *local* effects within 2 km of subway stations, which is different from the estimates of city-wide effects in the density specification discussed earlier. The impact is likely to be larger in the areas closer to subway stations due to the stronger impact on travel mode choices. Therefore, we expect the estimates from the DID to be larger than the estimated impacts from the IV method using the density measure, which is confirmed by our empirical findings (to be discussed later).[16]

Following a general framework by Bertrand et al. (2004) and Hansen (2007) with multiple groups and time periods, the basic DID framework is specified as

$$\begin{aligned}\ln(Air\,Pollution_{it}) = \theta Treated_{it} \times \mathbf{1}(Post_t) + Monitor_i + Trend_{it} + Weather_t \boldsymbol{\beta} \\ + Monitor_i \times Driving_t + Year_t + Season_t + DoW_t + Holiday_t + \varepsilon_{it},\end{aligned} \tag{2}$$

where $Treated_{it}$ is a treatment indicator that takes the value of 1 if monitor i is within 2 km of any subway stations that were opened on date τ ($\tau - 60 \le t \le \tau + 60$). $\mathbf{1}(Post_t)$ is a dummy variable indicating whether an observation is within 60 days *after* opening of these new subway stations, that is, $\tau \le t \le \tau + 60$. The parameter of interest is θ which captures the impact of the subway opening on air pollution for areas in the vicinity of the new subway stations within 60 days after the opening. Other control variables are defined as in Equation (1).

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[14] A quote from the article "The birth of the Beijing subway: Premier Zhou said that the preparation of the subway is to prepare for the battle" well explains the situation that China faced back in the 1950s, "In June 1950, the new China, which was just half a year after the founding of the People's Republic of China, was forced to become involved in the Korean War. At the same time, the US Seventh Fleet entered the Taiwan Strait …. In such an international situation, war preparedness should be the first factor to be considered in Beijing's urban planning." http://discovery.cctv.com/20070926/100879.shtml.

[15] The walking and biking distances are approximated based on the Guideline of Designing and Planning for Areas along Urban Rail from Ministry of Housing and Urban-Rural Development of the People's Republic of China, and Yang et al. (2018b). We also conduct a spatial lag analysis to determine the 2 km cut-off for the treated and 20 km cut-off for the control groups. The results are available upon request.

[16] To the extent that the opening of a subway station could impact the traffic flow of the whole city including areas 20 km away, the DID approach confounds control with treatment and could underestimate the true impact. Indeed, when we define the control group as the monitoring stations 15 km away from a subway station and shrink the buffer zone accordingly, we find a smaller impact, consistent with the intuition above. We choose 20 km to reduce the potential bias.

The key assumption of the DID is that, in the absence of a new subway opening, air quality in the treatment and control groups follow parallel trends. Most monitoring stations in the control group are in the suburban districts of the city as shown in Fig. 3. One may be concerned that those monitors in the control group may be too far away from the city center and thus would have different trends from those in the treatment group.

We take two strategies to address this concern. Our first strategy takes advantage of the staggered rollout design of the subway lines. We use the monitors that are located 20 km farther from the new subway stations but within 2 km distance of subway stations either opened in the past or to be opened in the future as the control group. Because both the treatment and control groups contain only monitoring stations that are close to subway stations, the two groups likely share similar (observed and unobserved) characteristics. The underlying assumption of this method is the randomness of the opening date.

Second, we use event study analysis to show the parallel trends hold for pre-opening periods in general. We divide the 120-day time window around opening dates into twelve 10-day intervals (six pre-opening periods $n = -5, -4, \ldots, 0$, and six post-opening periods $n = 1, 2, \ldots, 6$) and run the following regression:

$$\ln(Air\,Pollution_{it}) = \sum_{n \neq 0} \delta_n P_t(n) \times Treated_{it} + Monitor_i + Trend_{it} + Weather_t \boldsymbol{\beta} + Monitor_i \times Driving_t + Year_t + Season_t + DoW_t + Holiday_t + \varepsilon_{it} \tag{3}$$

where $P_t(n) = \mathbf{1}[\tau + 10 \cdot (n-1) \leq t \leq \tau + 10 \cdot n]$, indicating interval n. The base interval is the 10-day intervals before the opening dates (i.e., $n = 0$).

Table 6 (and Fig. 5) presents the coefficient estimates of δ_n. The results support the parallel trends assumption in general: compared with the base interval (10-day window before opening dates), the subsequent changes in air quality between the treatment and control groups are not significantly different for four out of the five pre-opening intervals in the specification

Table 6
Parellel trend test.

	Dependent variable: $\ln(Air\,Pollution_{it})$			
	(1)	(2)	(3)	(4)
$\mathbf{1}(Distance_{ij} \leq 2\text{ km}) \times \mathbf{1}(\tau - 60 \leq t < \tau - 50)$	−0.080	−0.099	−0.067	−0.076
	(0.061)	(0.061)	(0.062)	(0.083)
$\mathbf{1}(Distance_{ij} \leq 2\text{ km}) \times \mathbf{1}(\tau - 50 \leq t < \tau - 40)$	−0.147***	−0.158***	−0.147***	−0.157***
	(0.043)	(0.044)	(0.045)	(0.056)
$\mathbf{1}(Distance_{ij} \leq 2\text{ km}) \times \mathbf{1}(\tau - 40 \leq t < \tau - 30)$	−0.010	−0.022	−0.022	−0.034
	(0.049)	(0.051)	(0.052)	(0.058)
$\mathbf{1}(Distance_{ij} \leq 2\text{ km}) \times \mathbf{1}(\tau - 30 \leq t < \tau - 20)$	−0.065	−0.076	−0.088*	−0.095
	(0.050)	(0.050)	(0.052)	(0.060)
$\mathbf{1}(Distance_{ij} \leq 2\text{ km}) \times \mathbf{1}(\tau - 20 \leq t < \tau - 10)$	−0.029	−0.044	−0.063	−0.064
	(0.045)	(0.047)	(0.047)	(0.054)
$\mathbf{1}(Distance_{ij} \leq 2\text{ km}) \times \mathbf{1}(\tau < t \leq \tau + 10)$	−0.090*	−0.102**	−0.062	−0.054
	(0.048)	(0.049)	(0.045)	(0.056)
$\mathbf{1}(Distance_{ij} \leq 2\text{ km}) \times \mathbf{1}(\tau + 10 < t \leq \tau + 20)$	0.016	0.000	0.041	0.034
	(0.053)	(0.053)	(0.051)	(0.061)
$\mathbf{1}(Distance_{ij} \leq 2\text{ km}) \times \mathbf{1}(\tau + 20 < t \leq \tau + 30)$	−0.178***	−0.190***	−0.178***	−0.176***
	(0.052)	(0.052)	(0.052)	(0.062)
$\mathbf{1}(Distance_{ij} \leq 2\text{ km}) \times \mathbf{1}(\tau + 30 < t \leq \tau + 40)$	−0.256***	−0.267***	−0.277***	−0.274***
	(0.053)	(0.053)	(0.054)	(0.063)
$\mathbf{1}(Distance_{ij} \leq 2\text{ km}) \times \mathbf{1}(\tau + 40 < t \leq \tau + 50)$	−0.172***	−0.185***	−0.225***	−0.227***
	(0.057)	(0.057)	(0.056)	(0.064)
$\mathbf{1}(Distance_{ij} \leq 2\text{ km}) \times \mathbf{1}(\tau + 50 < t \leq \tau + 60)$	−0.044	−0.054	−0.112**	−0.116*
	(0.051)	(0.051)	(0.053)	(0.063)
Time Window (days)	$\tau \pm 60$	$\tau \pm 60$	$\tau \pm 60$	$\tau \pm 60$
Weather Controls	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Monitor FE	Y	Y	Y	Y
Monitor FE × Driving	N	Y	Y	Y
Monitor FE × Trend	N	N	Y	Y
Staggered Rollout	N	N	N	Y
N	17231	17231	17231	3314
R^2	0.53	0.53	0.54	0.56

Note: Each column reports results from an OLS regression where the dependent variable is ln(*Air Pollution*) and the key explanatory variables are the treatment dummies (the interaction of each 10 days within the 60-day time window around the opening dates and there is a new subway station within 2 km from the monitoring station). The control group is the monitors outside 20 km. The unit of observation is monitor-day. Column (4) relies on the staggered rollout. The weather controls include daily variables: temperature (C^0), relative humidity (%), precipitation (mm), wind speed (km/h), sets of dummies for wind direction and the interactions with the wind speed, dummies for rain, snow, storm, fog. The time fixed effects include year, season, day-of-week, holiday-of-sample dummies. Parentheses contain standard errors clustered at the day level. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

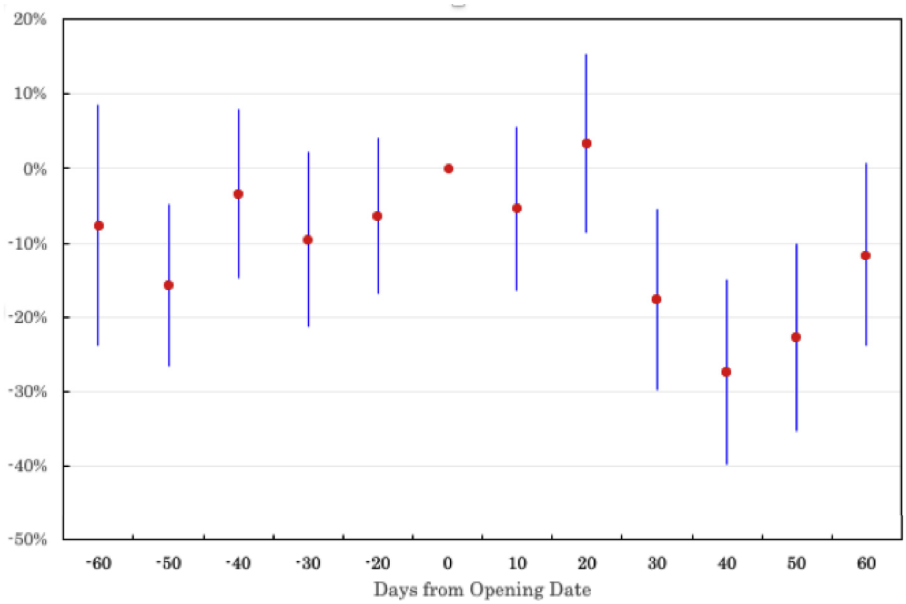

Fig. 5. Event study analysis of subway openings.

exploiting staggered rollout design (Column 4). In the specification that does not exploit the staggered rollout design (Column 3), three out of the five pre-opening intervals show parallel trends, with the base interval and the parallel trends assumption only being marginally rejected in one of the remaining two intervals. In contrast, we find statistically significant effects of air pollution reduction in four out of six post-opening intervals for the same two specifications (Columns 3 and 4).

One additional identification concern may arise from air pollution induced by subway construction, which differs between the treatment and the control group. The construction of a subway station involves both underground and ground work, which may generate construction dust and worsen the air quality. If the construction leads to higher pollution levels close to new subway stations before opening dates, the DID framework could mistake the pollution reduction from the mere completion of the construction itself as the impact of the subway expansion and hence overestimate the true impact. However, this concern is mitigated because under the national standard of subway construction in China, every subway line is subject to an intensive trial run over a three-month period during which the subway train is tested after the ground work has been finished completely.[17] Since our DID analysis focuses on the 120-day window around opening dates during which the subway construction is already completed, we do not expect construction dust to confound our results.

We estimate two alternative specifications to relax the assumption of uniform effects of subway opening across opening dates and stations. First, we allow the impact to vary by number of days after the subway opening, as specified in Equation (4).

$$\begin{aligned}\ln(Air\,Pollution_{it}) = {} & \psi_1 Treated_{it} \times \mathbf{1}(Post_t) + \psi_2 Treated_{it} \times \mathbf{1}(Post_t) \times Days_t + \psi_3 Treated_{it} \\ & \times \mathbf{1}(Post_t) \times Days_t^2 + Monitor_i + Trend_{it} + Weather_t\boldsymbol{\beta} + Monitor_i \times Driving_t \\ & + Year_t + Season_t + DoW_t + Holiday_t + \varepsilon_{it} \end{aligned} \tag{4}$$

where $Days_t$ is the number of days after the opening of the subway station. This specification allows the effect to occur gradually since it may take time for commuters to adjust their travel modes.

In the second specification, we examine the heterogeneity of treatment effects by allowing the impact to differ based on the number of new subway stations within the vicinity of the treated monitors as in Equation (5).

$$\begin{aligned}\ln(Air\,Polution_{it}) = {} & \eta N_{it} \times Treated_{it} \times \mathbf{1}(Post_t) + Monitor_i + Trend_{it} + Weather_t\boldsymbol{\beta} \\ & + Monitor_i \times Driving_t + Year_t + Season_t + DoW_t + Holiday_t + \varepsilon_{it} \end{aligned} \tag{5}$$

where N_{it} is the number of subway stations opened at date τ ($\tau - 60 \le t \le \tau + 60$) within the 2 km distance of the monitor i. This specification captures the notion that when more subway stations are located nearby, commuters are more likely to use the subway to reach their destinations and hence to reduce driving and air pollution more in the vicinity areas.

[17] The first phase of the trail run process has no passengers on board and during the second phase of the process, typically the last 20 days of the process, the subway with passengers (not the public) will be tested following the scheduled time and route.

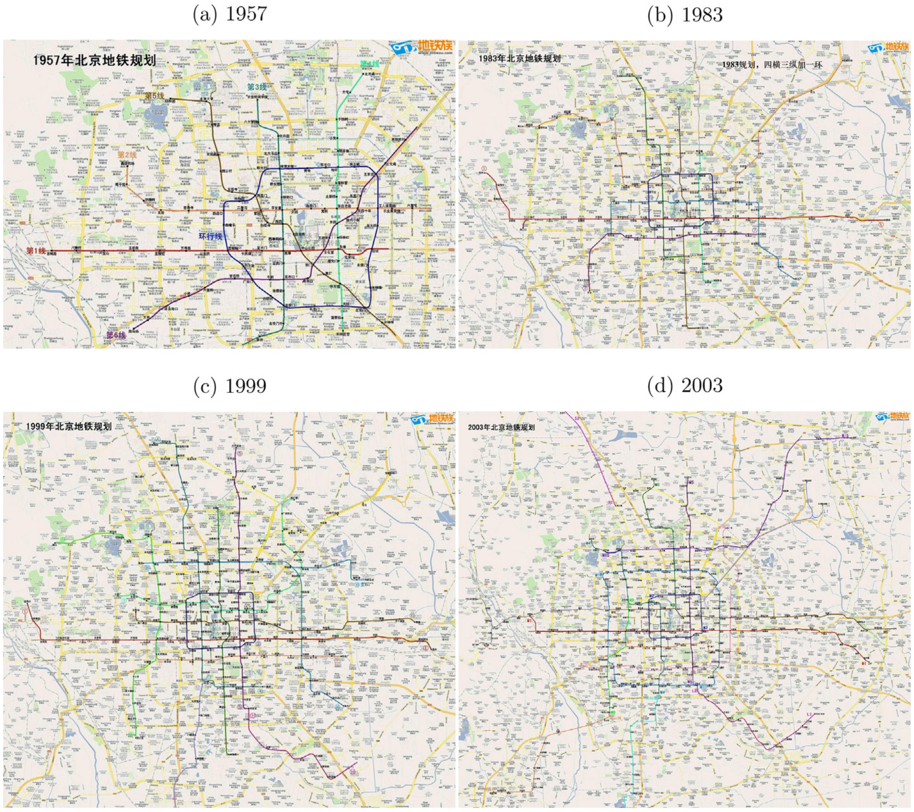

Fig. 6. Historical construction plans of the Beijing subway system.

4. Empirical results

In this section, we first present the estimated impacts of subway expansion on air quality using the IV method and the DID method in the first two subsections. We then present the results from a benefit-cost analysis based on back-of-the-envelope calculations.

4.1. Estimates based on network density

Table 7 shows the OLS results using the continuous density measure shown in Equation (1). The key variable is the standardized subway network density. We sequentially add weather variables, wind conditions, a rich set of location and time fixed effects, and the driving restriction policy as control variables. Column (1) does not have monitoring station fixed effects, and the result shows a positive correlation between subway density and the level of air pollution. This result is likely driven by the fact that the city center, where the subway network is denser, tends to have higher pollution levels. Once monitor fixed effects are included, the results show that higher subway density is associated with a lower level of air pollution. This negative relationship is robust across columns (2) to (4). Column (3) adds monitor fixed effects interacting with the driving restriction policy, while column (4) further includes a monitor-specific time trend. Adding the monitor-specific time trend helps to alleviate the concern about the endogenous location of subway lines. Subway lines may tend to be placed in areas with faster projected growth in economic activities (and hence more air pollution); without controlling for this, the impact of subway expansion on air quality would be underestimated, as confirmed by the results in columns (3) and (4).[18]

The results from the full model (column (4) of Table 7) suggest that a one standard-deviation increase in subway density reduces the air pollution level by 1.5 percent. This estimation exploits the variation in network density and air pollution across space and locations. It can be interpreted as the longer term impact, when we compare it with estimates from the DID framework

[18] We have also tried two alternate monitor-specific time trends: time squared and time cubed. The OLS results are robust to the order of the time trend, we find similar estimates with monitor-specific squared time trend and monitor-specific cubed time trend.

Table 7
OLS: The impact of subway network density on air pollution.

	Dependent variable: ln(*Air Pollution$_{it}$*)			
	(1)	(2)	(3)	(4)
$Density_{it}/\sigma$	0.049***	−0.006***	−0.007***	−0.015***
	(0.001)	(0.002)	(0.002)	(0.003)
Temperature (^{0}C)	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Relative humidity (%)	0.009***	0.009***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Rainfall/snow (mm)	−0.002*	−0.002*	−0.002*	−0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Wind speed (m/s)	−0.071**	−0.071**	−0.072**	−0.071**
	(0.031)	(0.031)	(0.031)	(0.031)
Monitor FE	N	Y	Y	Y
Monitor FE × Driving	N	N	Y	Y
Monitor FE × Trend	N	N	N	Y
N	86758	86758	86758	86758

Note: Each column reports results from an OLS regression where the dependent variable is ln(*Air Pollution*) and the key explanatory variable is the standardized subway network density $Density_{it}/\sigma$. Subway network density in a given location is defined as the weighted sum of subway stations weighted by the squared inverse distance from the location to each subway station in the network. The unit of observation is monitor-day. The weather controls include dummies for daily rain, snow, storm, fog. All columns have controlled for weather, wind directions, and a set of time fixed effects (Year, Season, Day of Week and holidays). Parentheses contain standard errors clustered at the day level. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

presented in the next section or from the literature, which typically relies on a shorter time window around the intervention to address confounding factors.

The weather variables have intuitive signs: high temperature and humidity are associated with a higher level of air pollution while rainfall/snow and wind are associated with a lower level of air pollution. High temperature can lead to faster formation of ground-level ozone and fine particulate matter while high humidity (without precipitation) makes it difficult for the natural air current to dissipate the pollutants. Precipitation in the form of rainfall or snow, as well as high wind, can help pollutants dissipate more quickly.

We address the potential endogeneity of network density measure using IV in Table 8. Column (1) is identical to column (4) in Table 7 to facilitate comparison. Column (2) instruments for the density variable with a hypothetical density measure based on the 2003 subway planning map and the actual opening date of each line. The impact from 2SLS is slightly larger in magnitude than that from OLS. Column (3) uses a random opening date during a six-month window around the observed opening date to construct the IV. This helps to address the concern that policymakers may choose the opening date partly based on the projected pollution level. In practice, the opening of a new subway is often celebrated with a ceremony at which high-level government officials from both the Beijing municipal government and the central government are present. Seven out of the 10 opening dates in our sample fall in the last few days of a calendar year. In addition to the coincidence of celebrating a new subway line opening together with the beginning of a new year, this choice of dates is also likely due to the fact that it is easier to gather high-level government officials during the public holidays.

Columns (4) to (6) of Table 8 use the ridership-weighted density measures in which higher weights are assigned to subway lines with larger ridership in the network. Column (4) comes from OLS, while columns (5) and (6) come from 2SLS. Column (5) uses the observed opening date to construct the IV, while column (6) randomizes the opening date. Column (6) produces slightly larger estimates than columns (4) and (5), suggesting that a one standard-deviation increase in population-weighted density reduces the level of air pollution by 3.5 percent. In both specifications with different density measures, 2SLS results are slightly larger than OLS estimates.

Table 9 translates the parameter estimates of the IV regression with observed opening dates (column 5 of Table 8) into the impact for each subway line. To estimate average subway density in Beijing, we calculate the subway network at the Traffic Administration Zone (TAZ) level.[19] Figs. 7 and 8 map the subway network density at the TAZ level at the end of 2007 (the year before our study period), 2009, 2011, 2013, and 2016. The subway network, which is denser at the city center, has been expanding rapidly with openings of new subway lines. For example, the opening of Line 6 (opened on December 30, 2012) increases the population-weighted density by 0.12 overall, which in turn leads to a 0.24 percent decrease in air pollution level. In the aggregate, the total 14 lines built from 2008 to 2016 result in a 1.01 percent decrease in air pollution in Beijing. Our estimates

[19] The city of Beijing is divided into 1911 Traffic Administration Zones (TAZs) for the purpose of city planning. Each TAZ has similar population size so the average subway density at the TAZ level is roughly equivalent to the population-weighted average of the density at the district level.

Table 8
IV: The impact of subway network density on air pollution.

(a) Standardized non-weighted density			
Dependent variable: ln(*Air Pollution*)	(1)	(2)	(3)
	OLS	IV	IV
		Second Stage	
$Density_{it}/\sigma$	-0.015^{***}	-0.020^{***}	-0.028^{***}
	(0.003)	(0.004)	(0.009)
Random Opening Dates		N	Y
		First Stage	
$Density_{it}/\sigma$ (2003 Planning)		0.789^{***}	0.651^{***}
		(0.004)	(0.012)
F-stat		48808	3160
(b) Standardized ridership-weighted density			
Dependent variable: ln(*Air Pollution*)	(4)	(5)	(6)
	OLS	IV	IV
		Second Stage	
$\widetilde{Density}_{it}/\sigma$ (ridership weighted)	-0.026^{***}	-0.024^{***}	-0.035^{***}
	(0.007)	(0.005)	(0.011)
Random Opening Dates		N	Y
		First Stage	
$Density_{it}/\sigma$ (2003 Planning)		0.655^{***}	0.520^{***}
		(0.004)	(0.012)
F-stat		57069	2605

Note: The last two columns report results from IV regressions where the dependent variable is ln(*Air Pollution*) and the key explanatory variable for Panel (a) is the standardized subway network density, $Density_{it}/\sigma$. Panel (b) shows results with the key explanatory variable as the density measure using line ridership as extra weights for the subway stations, $\widetilde{Density}_{it}/\sigma$. Column (2), (3), (5) & (6) report the result from IV regressions with different specifications. The instrument is the subway network density based on the 2003 subway plan map. Column (2) and (5) use the same opening dates for actual subway system and the IV. Column (3) and (6) assign random opening dates for lines in 2003 plan as the 3 months before or after the real opening dates. The unit of observation is monitor-day. All columns control for the daily weather variables: temperature (C^0), relative humidity (%), precipitation (mm), wind speed (km/h), sets of dummies for wind direction and the interactions with the wind speed, dummies for rain, snow, storm, fog; the time fixed effects: day-of-week, quarter-of-year, year, holiday-of-sample dummies; spatial fixed effects: dummies for air pollution monitoring stations and the interactions with the time trend and driving restriction policy dummies. Parentheses contain standard errors clustered at the day level. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

of the pollution reduction effect are smaller than that of Gendron-Carrier et al. (2018), who find a four percent reduction in air pollution after the opening of a new subway system. However, the majority of new subway systems considered in Gendron-Carrier et al. (2018) were the first subway lines in their corresponding cities, which could explain the larger estimated impacts than those in our case. In addition, studies using the DID or the regression discontinuity method tend to have larger estimates (Chen and Whalley, 2012; Zheng et al., 2017), as these estimates may capture a shorter term and more local impact than ours. This is consistent with our analysis using the DID method below, which shows a larger impact than the estimate based on the continuous density measure.

4.2. Difference-in-difference estimates

Table 10 presents the results from the basic DID model (Equation (2)). The results across columns exhibit similar patterns to those in Table 7. With the absence of monitoring station fixed effects in columns (1) to (3) of Table 10, air pollution level is positively associated with subway opening. After controlling for monitor fixed effects, Columns (4) to (6) provide similar estimates of the effects of subway opening on air pollution based on the DID model. The results from column (6) suggest that within a 60-day time window after a subway line's opening, the monitors in the vicinity (within 2 km) of subway stations exhibit a 7.7 percent reduction in air quality compared to the monitors outside the 20 km radius.

The DID specifications produce relatively larger impact estimates compared to those from the framework based on continuous density measures, likely for two reasons. First, the DID method focuses on a shorter-time window, while the method with density measures relies on variation during the whole data period. Thus, the DID estimates should be viewed as shorter-term impacts. Second, the DID method estimates the impacts of subway expansion on the areas within a 2- km radius of new subway lines which are likely larger than the city-wide effects estimated by the method with network density measures.

Table 11 reports regression results using different time windows (from 10 to 180 days) before and after the opening dates. The significant, negative estimates are not statistically different across 40- to 100-day windows (column 4 to 10). When we

Table 9
Marginal impact of subway expansion on air pollution.

Opening date	Cumulative Standardized Density		MarginalIncrease in Density		Marginal Reduction in air pollution (%)	
	non- weighted (1)	ridership-weighted (2)	non-weighted (3)	ridership-weighted (4)	non-weighted (5)	ridership-weighted (6)
Before 2008	0.230	0.201	–	–	–	–
July 19, 2008	0.307	0.300	0.077	0.098	0.154	0.236
Sep 28, 2009	0.365	0.366	0.057	0.066	0.115	0.157
Dec 30, 2010	0.432	0.380	0.068	0.015	0.135	0.035
Dec 31, 2011	0.459	0.391	0.027	0.010	0.054	0.025
Dec 30, 2012	0.577	0.515	0.118	0.125	0.237	0.299
May 5, 2013	0.595	0.532	0.017	0.016	0.035	0.039
Dec 28, 2013	0.604	0.535	0.010	0.004	0.020	0.009
Dec 28, 2014	0.697	0.575	0.093	0.040	0.185	0.095
Dec 26, 2015	0.726	0.587	0.029	0.012	0.058	0.029
Dec 31, 2016	0.735	0.589	0.009	0.002	0.018	0.005
Total			0.505	0.387	1.009	0.930

Note: Network density centered at a TAZ is defined as the weighted sum of subway weighted by the squared inverse distance from the centroid of the TAZ to each subway station operating in the network as of the opening date. It is standardized by dividing its standard deviation. The ridership-weighted density is the reweight of the density by ridership of subway line. Standard deviations of the both densities are $\sigma = 16.38$ and $\widetilde{\sigma} = 19.62$ respectively. All density measures are averaged over TAZs for each opening date.

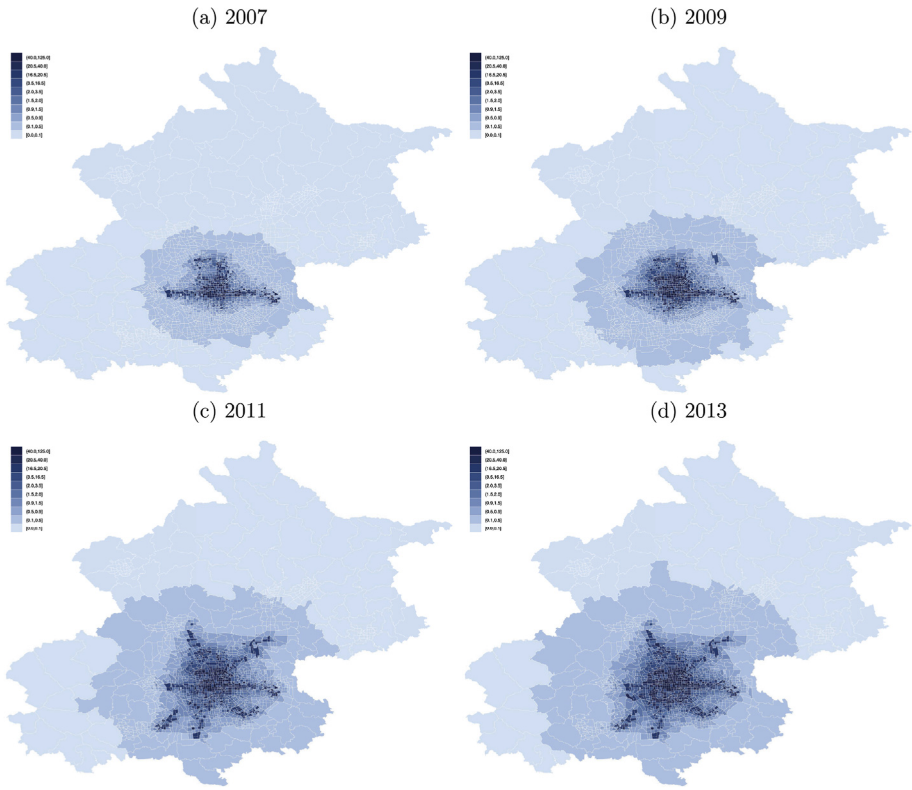

Fig. 7. Subway Expansion and Network Density at the TAZ level.

increase the window to 110 days and longer, however, the average effect seems to fade away. This is consistent with the notion that it may take some time for commuters to adjust their travel modes in the short term and hence for the impact on air pollution to be materialized. In the longer term, reduced traffic congestion could lead to additional driving demand, mitigating the initial reduction of air pollution. This dynamic is consistent with traffic diversion in the short-term and with induced traffic demand in the longer-term, as discussed in the introduction.

Table 12 shows the effect under a continuous measure of the time variables. We interact the treated group indicator with the linear and the quadratic term of days post-opening, respectively. We also compare the specifications under two different time windows (60 days and 120 days around the opening dates). The results from our model specifications with the quadratic term of days post-opening (columns 2 and 4) suggest that the effect of subway opening on air pollution is non-linear. The subway

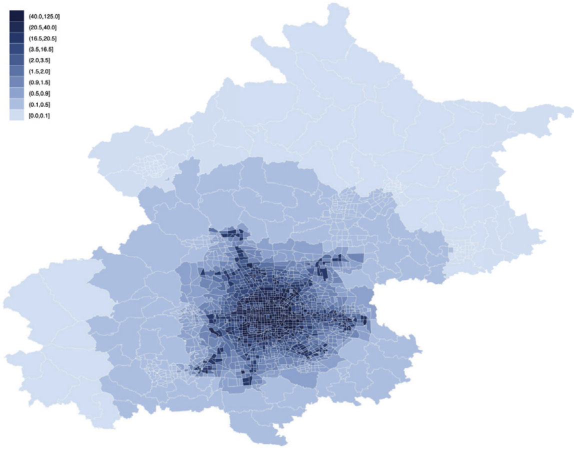

Fig. 8. Beijing Subway Network Density at the TAZ level as of 2016.

Table 10
Difference-in-difference estimates with a fixed time window.

	Dependent variable: ln(*Air Pollution*)					
	Without Monitor FE			DID		
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated_{it} \times \mathbf{1}(Post_t)$	0.105***	0.082***	0.099***	−0.073***	−0.075***	−0.077***
	(0.026)	(0.020)	(0.013)	(0.019)	(0.019)	(0.018)
Temperature (^0C)		−0.011***	0.010***	0.010***	0.010***	0.012***
		(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Relative humididy (%)		0.008***	0.015***	0.015***	0.015***	0.015***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation (mm)		−0.007*	−0.006*	−0.006*	−0.007*	−0.006
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Wind speed (m/s)		−0.078*	−0.105***	−0.104***	−0.106***	−0.103***
		(0.042)	(0.034)	(0.034)	(0.034)	(0.034)
Constant	4.434***	4.144***	3.727***	3.846***	3.854***	3.765***
	(0.018)	(0.104)	(0.140)	(0.141)	(0.153)	(0.153)
Time Window (days)	$\tau \pm 60$	$\tau \pm 60$	$\tau \pm 60$	$\tau \pm 60$	$\tau \pm 60$	$\tau \pm 60$
Weather controls	N	Y	Y	Y	Y	Y
Wind Directions	N	Y	Y	Y	Y	Y
Wind Directions × Speed	N	Y	Y	Y	Y	Y
Year FE	N	N	Y	Y	Y	Y
Season FE	N	N	Y	Y	Y	Y
Day of Week FE	N	N	Y	Y	Y	Y
Monitor FE	N	N	N	Y	Y	Y
Monitor FE × Driving	N	N	N	N	Y	Y
Monitor FE × Trend	N	N	N	N	N	Y
N	18214	17231	17231	17231	17231	17231
R^2	0.00	0.29	0.45	0.52	0.53	0.54

Note: Each column reports results from an OLS regression where the dependent variable is ln(*Air Pollution*) and the key explanatory variable the interaction of treatment and post-opening. Columns (4) to (6) show the DID estimates with different sets of controls. The treatment group is defined as the monitoring stations within 2 km of a new subway line while the control group is defined as the monitoring stations more than 20 km away from the new subway line. The unit of observation is monitor-day. The weather controls include dummies for rain, snow, storm, fog. Parentheses contain standard errors clustered at the day level. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

opening begins to have a negative effect on air pollution after approximately 15–20 days; the magnitude of the effect then increases at a decreasing rate, with a turning point being around 50–60 days, after which the effect diminishes.

Table 13 presents results from the DID specification which accounts for the number of subway stations in the vicinity of treated monitors. The result shows that one additional subway station added to the vicinity of a monitor reduces air pollution by 2–4.1 percent, depending on model specifications. Compared to the IV method based on the network density measure, the DID method yields qualitatively the same results but considerably larger point estimates. Take the previous example of Line 6. The opening of Line 6 improves air quality in Beijing by 0.70 percent (assuming no effects on buffered locations) to 6.04 percent (assuming the buffered locations have the same impact as the treated locations). This comparison reflects the interplay of the two countervailing forces: the traffic division effect of public transit investment (the Mohring effect), and the induced demand

Table 11
Difference-in-difference estimates with varying time windows.

	Dependent variable: ln*AQI*					
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated_{it} \times \mathbf{1}(Post_t)$	−0.046	−0.031	−0.029	−0.052***	−0.057***	−0.052***
	(0.038)	(0.025)	(0.020)	(0.018)	(0.016)	(0.015)
Time Window (days)	$\tau\pm10$	$\tau\pm20$	$\tau\pm30$	$\tau\pm40$	$\tau\pm50$	$\tau\pm60$
Time Window (days)	(7)	(8)	(9)	(10)	(11)	(12)
	−0.066***	−0.062***	−0.075***	−0.047***	−0.022	−0.015
	(0.014)	(0.013)	(0.013)	(0.016)	(0.016)	(0.016)
	$\tau\pm70$	$\tau\pm80$	$\tau\pm90$	$\tau\pm100$	$\tau\pm110$	$\tau\pm120$
Time Window (days)	(13)	(14)	(15)	(16)	(17)	(18)
	−0.008	−0.007	−0.009	−0.009	−0.019	−0.023
	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
	$\tau\pm130$	$\tau\pm140$	$\tau\pm150$	$\tau\pm160$	$\tau\pm170$	$\tau\pm180$

Note: Each column reports results from an OLS regression using different time windows ((1) to (18): $Open_t = \tau\pm10, \tau\pm20, \ldots, \tau\pm60, \ldots, \tau\pm180$-day) where the dependent variable is ln(*Air Pollution*) and the key explanatory variable is the interaction of the time window dummy and the treated group indicator . The May 5th, 2013 opening is dropped from the sample to avoid overlapping events and to extend the time window. The treatment group is defined as the monitoring stations within 2 km of a new subway line while the control group is defined as the monitoring stations more than 20 km away from the new subway line. The unit of observation is monitor-day. All columns control for the daily weather variables: temperature (C^0), relative humidity (%), precipitation (mm), wind speed (km/h), sets of dummies for wind direction and the interactions with the wind speed, dummies for rain, snow, storm, fog; the time fixed effects: day-of-week, quarter-of-year, year, holiday-of-sample dummies; spatial fixed effects: dummies for air pollution monitoring stations and the interactions with the time trend and driving restriction policy dummies. Parentheses contain standard errors clustered at date level. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 12
Difference-in-difference estimates with continuous time measurement.

	Dependent variable: ln*AQI*			
	(1)	(2)	(3)	(4)
$Treated_{it} \times \mathbf{1}(Post_t)$	0.075**	0.151***	−0.001	0.110***
	(0.036)	(0.056)	(0.026)	(0.041)
$Treated_{it} \times \mathbf{1}(Post_t) \times Days_{it}$	−0.004***	−0.012***	−0.000	−0.006***
	(0.001)	(0.004)	(0.000)	(0.002)
$Treated_{it} \times \mathbf{1}(Post_t) \times Days^2_{it}/100$		0.013*		0.005***
		(0.007)		(0.001)
Time Window (days)	$\tau\pm60$	$\tau\pm60$	$\tau\pm120$	$\tau\pm120$
N	15467	15467	30933	30933
R^2	0.56	0.56	0.47	0.47

Note: Each column reports results from an OLS regression where the dependent variable is ln(*Air Pollution*). The treatment group is defined as the monitoring stations within 2 km of a new subway line while the control group is defined as the monitoring stations more than 20 km away from the new subway line. The unit of observation is monitor-day. All columns control for the daily weather variables: temperature (C^0), relative humidity (%), precipitation (mm), wind speed (km/h), sets of dummies for wind direction and the interactions with the wind speed, dummies for rain, snow, storm, fog; the time fixed effects: day-of-week, quarter-of-year, year, holiday-of-sample dummies; spatial fixed effects: dummies for air pollution monitoring stations and the interactions with the time trend and driving restriction policy dummies. Parentheses contain standard errors clustered at date level. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

effect. The second channel takes longer to occur and dampens the positive impact on air quality improvement observed in the short term. Nevertheless, our estimates suggest that the first channel is the dominant force in the longer run.

4.3. Cost-benefit analysis

This section presents a back-of-the-envelope analysis on the benefit of subway expansion through two channels. The first benefit is on human health including both mortality and morbidity from improved air quality. The second benefit comes from congestion relief and the value of saved travel time for commuters.

Our empirical analysis finds that subway expansion leads to statistically significant improvement in air quality. Table 9 shows the estimated air quality improvement due to each subway line based on the benchmark specification (based on the IV results in Table 8). The population-weighted air quality improvement ranges from 0.02 percent by Line 16 opened on December 31, 2016 to 0.24 percent by Line 6 opened on December 30, 2012. Recent literature from both epidemiology and economics has shown

Table 13
Difference-in-difference estimates with heterogenous effect.

	Dependent variable: ln(*Air Pollution*)			
	(1)	(2)	(3)	(4)
$N_{it} \times Treated_{it} \times \mathbf{1}(Post_t)$	−0.020***	−0.024***	−0.032***	−0.041**
	(0.007)	(0.007)	(0.007)	(0.018)
Temperature (^0C)	0.010***	0.010***	0.012***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
Relative humidiy (%)	0.015***	0.015***	0.015***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation (mm)	−0.006*	−0.007*	−0.006	−0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Wind speed (m/s)	−0.104***	−0.106***	−0.103***	−0.130***
	(0.034)	(0.034)	(0.034)	(0.038)
Time Window (days)	$\tau\pm60$	$\tau\pm60$	$\tau\pm60$	$\tau\pm60$
Weather Controls	Y	Y	Y	Y
Wind Directions	Y	Y	Y	Y
Wind Directions × Speed	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Season FE	Y	Y	Y	Y
Day of Week FE	Y	Y	Y	Y
Monitor FE	Y	Y	Y	Y
Monitor FE × Driving	N	Y	Y	Y
Monitor FE × Trend	N	N	Y	Y
Staggered Rollout	N	N	N	Y
N	17231	17231	17231	3314
R^2	0.52	0.53	0.54	0.55

Note: Each column reports results from an OLS regression where the dependent variable is ln(*Air Pollution*) and the key explanatory variable is the interaction of treatment, post-opening, and number of new subway stations within 2 km of each monitor. The control group is defined as the monitoring stations more than 20 km away from the new subway line. The unit of observation is monitor-day. Column (4) relies on the staggered rollout. The weather controls include dummies for rain, snow, storm, fog. Parentheses contain standard errors clustered at date level. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

that the long-term exposure to airborne particulates can lead to elevated mortality especially among infants and morbidity due to cardiorespiratory diseases (Chay and Greenstone, 2003; Currie and Neidell, 2005; Currie and Walker, 2011; Knittel et al., 2015; Greenstone and Hanna, 2014; He et al., 2016; Ebenstein et al., 2017).

To calculate the mortality impact of subway expansion, we take the estimates from Ebenstein et al. (2017) who study the impact of long-term exposure to airborne particulate matter on mortality using a regression discontinuity design. They find that a 10-μg/m^3 increase in PM_{10} increases cardiorespiratory mortality by 8 percent; this impact varies across age cohorts but not across gender. Following the analysis in Barwick et al. (2018) to monetize the mortality impact, the mortality cost amounts to \$13.38 billion across the Chinese population from a 10-μg/m^3 increase in PM_{10}, or \$64.9 per household in Beijing when adjusted for the Beijing per capita income (in 2015 dollars). The morbidity cost of air pollution comes from Barwick et al. (2018), who provide the first comprehensive analysis of the morbidity cost in China based on the universe of credit and debit card spending. They find that the morbidity cost from a 10-μg/m^3 increase in $PM_{2.5}$ is \$20.2 (in 2015 dollars) per household for China.[20]

The congestion relief benefit comes from the value of the saved commuting time. Using a regression discontinuity design, Yang et al. (2018a,b) estimate that each new subway line reduces travel delay by an average of 15 percent based on the subway lines that opened between 2009 and 2015. The Beijing Annual Transportation Report shows that the average traffic delay time is around 20 min per hour. We assume that these delays occur during the peak hours (7am–9am and 5pm–7pm) on the week-days and that approximately two million commuters (who travel by cars and buses) are affected. The value of time (VOT) for automobile travel is often assumed to be half of the market wage (Parry and Small, 2009), which is 62.98 Yuan per hour (\$9.5 per hour) based on the monthly wage of 10,077 Yuan.

Panel (a) of Table 14 presents the cost-benefit calculations during a 10-year period after the opening of each subway line. The cost includes both the upfront construction cost and the operating cost (Column 1). We discount the operating cost and the benefit at a 5 percent annual discount rate. The total cost from all the subway lines during the sample period is \$56.3 billion (with the construction cost being \$46.7 billion). The health benefit amounts to \$0.64 billion (Column 2), or 1.13 percent of the total cost (Column 4), while the benefit from congestion relief is \$26.9 billion (Column 6), or 48 percent of the total cost (Column 8). Panel (b) of Table 14 presents the cost-benefit calculations during a 20-year period where the benefit

[20] We follow the emerging literature on the morbidity costs of air pollution (Deschenes et al., 2017; Barwick et al., 2018), which estimate that the morbidity costs could amount to about two thirds of the mortality costs. Landrigan et al. (2018) summarized a series of studies that suggest that the morbidity costs resulting from pollution-related disease might conservatively increase mortality costs by 10–70%, and some individual country studies suggest that the increment might be even greater: 25% for Colombia, 22–78% for China, and 78% for Nicaragua.

Table 14
Cost-benefit analysis of subway expansion.

Opening Date	Total Cost	Health Benefit				Congestion Benefit			
	Billion $	Billion $		% of Cost		Billion $		% of Cost	
		lower VSL = 2.3	upper VSL = 8.7	lower VSL = 2.3	upper VSL = 8.7	lower VOT = 0.5	upper VOT = 1.0	lower VOT = 0.5	upper VOT = 1.0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(a) 10 Years of Operation									
Jul 19, 2008	5.69	0.08	0.26	1.45	4.58	2.69	5.37	47.28	94.46
Sep 28, 2009	3.61	0.06	0.20	1.79	5.65	2.69	5.37	74.52	148.66
Sep 30, 2010	7.05	0.08	0.25	1.14	3.61	2.69	5.37	38.16	76.23
Sep 31, 2011	5.19	0.03	0.10	0.60	1.90	2.69	5.37	51.83	103.56
Sep 30, 2012	10.37	0.13	0.42	1.28	4.04	2.69	5.37	25.94	51.80
May 5, 2013	3.15	0.03	0.08	0.84	2.66	2.69	5.37	85.40	170.51
Sep 28, 2013	1.96	0.02	0.05	0.77	2.43	2.69	5.37	137.24	274.73
Sep 28, 2014	11.58	0.15	0.47	1.28	4.04	2.69	5.37	23.23	46.39
Sep 26, 2015	2.94	0.04	0.14	1.49	4.70	2.69	5.37	91.50	182.43
Sep 31, 2016	4.81	0.01	0.04	0.26	0.81	2.69	5.37	55.93	111.73
Total	56.34	0.64	2.01	1.13	3.57	26.90	53.70	63.10	95.34
(b) 20 Years of Operation									
Jul 19, 2008	6.21	0.13	0.40	2.05	6.47	4.15	8.29	66.83	133.50
Sep 28, 2009	4.14	0.10	0.32	2.41	7.62	4.15	8.29	100.24	200.39
Dec 30, 2010	7.57	0.12	0.39	1.64	5.18	4.15	8.29	54.82	109.51
Dec 31, 2011	5.71	0.05	0.15	0.84	2.67	4.15	8.29	72.68	145.18
Dec 30, 2012	10.89	0.20	0.65	1.88	5.94	4.15	8.29	38.11	76.10
May 5, 2013	3.67	0.04	0.13	1.11	3.52	4.15	8.29	113.08	225.65
Dec 28, 2013	2.48	0.02	0.07	0.94	2.96	4.15	8.29	167.34	334.42
Dec 28, 2014	12.10	0.23	0.72	1.89	5.96	4.15	8.29	34.30	68.51
Dec 26, 2015	3.47	0.07	0.21	1.95	6.16	4.15	8.29	119.60	239.04
Dec 31, 2016	5.33	0.02	0.06	0.36	1.13	4.15	8.29	77.86	155.51
Total	71.22	0.98	3.11	1.38	4.36	41.50	82.90	84.49	116.41

Note: All the monetary terms are in 2015 dollars and discounted by an annual discount rate of 5%. The total cost includes both the construction cost and the operating cost. The construction cost accounts for 82.9% of the total cost during a 10-year period for the lines in the sample period and 65.6% for the period of 20 years. The health benefit includes the saving from mortality and morbidity costs. The lower bound health benefit calculations are based on the Value of a Statistical Life (VSL) of $2.3 million (in 2015) as in Ashenfelter et al. (2004). The upper bound health benefits are based on the central estimate of $8.7 million as recommended by U.S. EPA. The savings from congestion relief are calculated based on the reduced time delay by subway opening using estimates from Yongchong Yang et al. (2018). The lower bound of congestion cost saving assumes the value of time (VOT) to be 50% of the wage, and the upper bound assumes 100% of wage as the VOT.

from health and congestion relief accounts for 1.38 percent and 58 percent of the total cost, respectively. The analysis suggests that the health benefit from improved air quality is a relatively small portion compared to the overall benefit of subway expansion.

However, our benefit estimates in Columns (2), (4), (6), and (8), are conservative for three reasons. First, the mortality benefit is based on the Value of a Statistical Life (VSL) of $2.27 million (in 2015) from (Ashenfelter et al., 2004), rather than the central estimate of $8.7 million figure recommended by the U.S. EPA. Second, the value of time is assumed to be 50 percent of the wage, rather than 100 percent of the hourly wage (Small, 2012; Wolff, 2014). Third, the benefit calculation includes neither the benefit from improved commute reliability nor the benefit from a larger choice set of travel modes (Small, 2005).

We then calculate an upper bound of the health benefit and congestion relief benefits in 10-year and 20-year respectively, presented in Columns (3), (5), (7), and (9). These estimates are based on the VSL of $8.7 million from the U.S. EPA and the VOT of 100 percent of hourly wage in Beijing. At the upper bound, the health benefit amounts to $2.01 billion or 3.57 percent of the total cost while the benefit from congestion relief is $53.71 billion or 95.34 percent of the total cost during a 10-year period. During a 20-year period, the upper bound of benefits from health and congestion relief accounts for 4.36 percent and 116.41 percent of the total cost respectively. Together, the total benefits from health and time saving alone exceed the costs during a 20-year timeframe, recognizing that subway systems could have a life span of at least several decades or over 100 years.[21]

Our analysis suggests that although the health benefit of subway expansion is nontrivial, it is much smaller than the benefits from congestion relief. Large sources of air pollution in Beijing include motor vehicle emissions, industrial activities, coal burning, and construction dust, as well as long-range transported pollution from nearby cities. According to Beijing Environmental Protection Bureau, automobiles are the largest source of $PM_{2.5}$, accounting for 22 percent in the whole city and about one third of the total in the urban core in 2012. The second largest source of $PM_{2.5}$ in 2012 is coal burning (17 percent), followed by construction site dusts (16 percent). Unless driving is substantially reduced, the impact on air quality improvement from infrastructure investment alone is likely to be small, especially when the road usage is not priced.

[21] London has the oldest subway system which started in 1890 and the New York City subway system began operation in 1904.

5. Conclusion

To address worsening air pollution and traffic congestion across urban areas in China, central and local governments are undertaking large investment in transportation infrastructure such as roads, rail, and subway systems. China's total investment in transportation infrastructure in 2014 amounted to 2.5 trillion yuan ($409 billion), about four percent of its GDP. Beijing has been leading the way among major cities in public transportation infrastructure by rapidly expanding its subway lines. Between 2002 and 2015, the Beijing municipal government invested nearly 300 billion Yuan (or USD 47 billion) on 16 new subway lines and Beijing now has the second longest subway network of 599 km in the world, after Shanghai.

While previous literature has examined the congestion relief function of public transportation, there is limited evidence regarding the impact of subway expansion on air quality. By leveraging fine-scale air pollution data and the rapid rollout of 14 new lines from 2008 to 2016 in Beijing, we find that the opening of new subway stations improves air quality from a variety of empirical specifications. An IV analysis based on the network density measure shows that a one standard-deviation increase in the density improves air quality by two percent. The 20-year total discounted health benefits of the subway expansion amounts to $1.0–3.1 billion due to reduced mortality and morbidity from improved air quality. Nevertheless, the benefit would only account for 1.4 to 4.4 percent of the total cost, including both the construction and operating cost. Our findings suggest that most of the cost from subway expansion needs to be justified from traffic congestion relief and other economy-wide impacts. Future research could examine the impact of subway expansion on the location choices of households, labor participation decisions, and firm entry and exit, all of which could have important implications on the broader economy.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2019.05.005.

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