The Effect of Subway Expansion on Air Quality: Evidence from Beijing*

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Major cities in China and many other fast-growing economies are expanding their subway systems 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 buildout of 14 new subway lines and 255 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. To address the potential endogeneity of the density measure due to endogenous subway location choices, we construct a minimal spanning tree (a hypothetical subway network) to sever as an instrumental variable. Our analysis shows that an increase in subway density by one standard deviation improves air quality by 2% in the long term 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 10-year period from reduced motality and morbity as a result of the subway expansion observed during the sample period amounts to $24.4 billion, or 43.3% of the total construction and operating cost.

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1 Introduction

Traffic congestion and air pollution are two pressing challenges in many developing and emerging countries. Based on real-time driving data in 390 cities in 48 countries in 2016, TomTom Traffic Index shows that among the top 20 most congested cities, all but one are from developing and emerging economies with eight of them from China. Meanwhile, the highest level of PM2.5 concentration was seen in East and South Asia such as Bangladesh, China, India, and the Persian Gulf in 2015. Ambient PM2.5 mainly emitted by automobiles is the leading environmental factor for death, accounting for about 4.2 million deaths in 2015, nearly 40% of which occurred in China.

To combat traffic congestion and air pollution, the Beijing municipal government has been investing heavily in transportation infrastructure such as buses, roads, and subway lines. From a global perspective, Beijing's rapid development of mass transit since 2007 is unprecedented. From 2007 to 2015, the total investment in transportation facilities amounted to over 430 billion Yuan (about USD 67 billion). During this period, 14 new subway lines and one airport expressway were constructed with a total length of 440 kilometer. The rapid subway expansion program is still ongoing in Beijing: another 12 subway lines are under construction and scheduled to open before the end of 2020 with a total length of nearly 378 kilometer. Similar large scale and rapid expansion of subway systems are taking place in other major cities throughout China.

Despite the huge investment in subway infrastructure in Beijing and other major cities in China, rigorous evaluation of impacts of subway expansion is lacking. We aim to partially fill this void by investigating the extent to which subway expansion works in addressing the air pollution problem. The expansion of the subway network could impact air quality through two main channels. 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)). In the long run, this traffic creation effect could undo the positive impact realized through the first channel. So the net effects of subway expansion on air quality are ambiguous in theory and should be investigated empirically.

Our main data set contains daily monitor-level Air Pollution Index (API) from 2008 to 2012 and Air Quality Index (AQI) in Beijing from 2013 to 2017 from 27 monitors that are consistently functioning during the sample period. We map the locations of the 27 monitoring stations and 345 subway stations opened by the end of 2016, among which 255 subway stations are opened during our sample period (2008 - 2016). We also collect data on a rich set of weather controls and transportation policies that could affect traffic conditions and/or air quality during the sample period.

The main empirical strategy examines how air quality across different locations in the city is affected by a density measure of subway network that varies over time and across space. The major identification concern stems from the potential endogeneity in location choices of the subway stations in that the locations are chosen based on the expectations of future traffic congestion and air quality in those areas. For example, subway stations might be located in areas with a faster projected growth in travel demand and deterioration in air quality, which would lead to an underestimation of the true impact of subay expansion on air quality.

To address this endogeneity concern, we construct a hypothetical subway network to instrument for the density measure following the appraoch in Faber (2014) for highway networks in China. The hypothetical network is a minimum spanning tree (MST) with the objective of serving all districts of Beijing (both central and suburban) while maintaining a certain level of connectivity across subway lines. Based on the map of the Beijing subway network, we first draw the same number of straight subway lines which cover the same areas and then reallocate the subway stations along the straight lines and keep the same transfering stations. We construct a density measure based on the hypothetical network as the IV for the observed density measure. With a rich set of temporal and spatial fixed effects, the IV results show that one standard-deviation increase in the subway density improves air quality by 2%. The estimates imply that the reduction in the pollution level ranges from 0.69% from line 16 (with a length of 20km) to 10% from line 6 (with a length of 78km).

To further examine the robustness of our results, we use a distance-based difference-in-differences (DD) method based on the assumption that the spatial spillover effect is local. We define the locations (of air quality monitors) within 2km of a subway station as the treatment group and the locations farther than 20km away from a subway station as the control group. The locations between 2km to 20km are used as a buffer zone and ares dropped in the analysis to avoid misclassifying the treatment status. We compare the air quality during the 60-day period right after the opening of a subway line with the 60-day period right before the opening between the treatment and the control group. The key identification assumption of DD is that in the absence of subway opening, air quality in the treatment and control group would follow similar trends. One may be concerned that subway construction could cause ground construction dust and worsen the traffic congestion, leading to an overestimation of the pollution reduction effect. However, this would not be a concern here because the safety regulations required a 3-month trial running period before opening a new subway line. So the physical construction had to end at least 3 months before the opening. The test on pre-treatment trends between the two groups reveals no statistically and economically significant difference.

Our analysis of alternative specifications suggests robust and significantly positive effects of subway expansion on air quality. The DD specification shows that subway expansion improves air quality in the vicinity (within 2k) of the new subway line by 7.5% relative to the area outside of the 20km radius within the 60-day time window. Allowing heterogenous effects over time, we show that the effect becomes significant after one month and largest around 60 days after opening. The DD specification considering heterogeneity in subway density gives consistent estimates with the IV estimates. Air quality improves further as more subway stations are built near a monitoring station: one additional subway station within the 2km radius of a monitor improves air quality by 3.1%. The pollution reduction effect of subway expansion is also significant economically.

Based on our empirical results, we conduct a back-of-the-envelope calculation on the benefit of subway expansion from improved health outcomes and reduced traffic congestion. The health benefit includes both mortality and mortality impacts while the benefit from traffic congestion relief stems from the value of reduced travel time for commuters. Our analysis shows that the subway expansion observed during our sample period can provide a total discounted health benefit of $24.4 billion during a 10-year period and $37.6 billion during a 20-year period, accounting for 43.3% and 52.8% of the total upfront construction cost and the total discounted operating cost during the same period. The benefit in terms of traffic congestion reduction is about twice as large as the health benefit.

Our paper adds to the small literature on the impact of subway expansion on air quality. Gendron-Carrier et al. (2018)provides a broad analysis about the impact of opening a new subway system on air pollution over 43 cities in the world with new subway systems opened during 2000 to 2014. By using the satellite aerosol optical depth data at a 10 km resolution range around the city centers, the paper estimates that particulate concentrations drop by 4% following a new subway system opening. The effect they argue persists as long as eight years. Chen and Whalley (2012) focus on the causal effect on air pollution from opening one subway line in Taipei. Following a regression discontinuity framework, they find that the opening of the Taipei Metro reduced air pollution from one key tailpipe pollutant, carbon monoxide by 5 to 15 percent. To our knowledge, our study is the first one that estimates the impact of subway expansion on air quality by leveraging fine-scale air pollution data and multiple subway lines within the same city.

The unprecedented expansion of Beijing's rapid subway expansion since 2007 provides a unique opportunity to examine the effects of marginal changes (e.g., small increases in the coverage of subway networks) in the transit network. Our study fills the void of the existing literature which either looked at the effect of the entire system shutdown (e.g., Anderson (2014)) or looked at the effect of a single transit line (e.g. Chen and Whalley (2012)). Our analysis leverages data that only became available to researchers recently and have not been explored. The rich spatial and temporal variation allows us to better identify the impacts across space and over time.

Our study has important policy implications. Subway construction requires large public funds and the benefit from improved air quality should enter the cost-benefit calculation of the urban planners. As rapid urbanization in developing countries has become a global trend, our study will also provide useful policy recommendations for developing countries in general.

The reminder of the paper is organized as follows. Section 2 discusses the background and related regulations. In Section 3, we introduce the data and presents summary statistics. Section 4 describes the empirical strategy. In Section 5, we discuss the estimation results and policy implications and Section 6 concludes.

2 Background and Data

In this section, we discuss the institutional background of the severe air pollution challenge and the fast expansion of the Beijing subway system. We then present the main datasets.

2.1 Air Pollution

In past decades, China has experienced unprecedented economic growth. From 1980 to 2016, the per capita GDP of China increased hugely from less than $200 to over $8000 in nominal terms according to the World Bank. Meanwhile, air quality in major urban cities in China, including Beijing, is deteriorating. Figure 1 shows the daily and annually PM2.5 concentrations in Beijing from 2008 to 2017. The average level is about twice the Chinese annual standard, and six to ten times the U.S. standard. [1]

A rich economic literature has shown the 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), etc.). The epidemiology literature has linked chronic obstructive pulmonary disease (COPD); ischaemic heart disease (IHD),

[1]The U.S. Environmental Protection Agency set the U.S. standard as 12 $\mu g/m^3$ annually and $35\mu g/m^3$ daily. The China MEP set the Chinese standard as 35 $\mu g/m^3$ annually and 75 $\mu g/m^3$ daily.

COPD and lung cancer (LC) to PM2.5 (Burnett (2014)). According to the Global Burden of Diseases, Outdoor air pollution contributed to 4.2 million premature deaths in the world in 2015 and 40% of that occurred in China.

The outdoor air pollution has primary sources at two levels, the elevated-level, such as power plants and the ground-level, such as traffic. The main cause for elevated-level air pollution is the economic transformation from agricultural to industrial which dramatically increased energy use in China, especially for coal. China has the highest energy consumption in the world by far, which accounts for one quarter of the world's total energy consumption and one half of the coal consumption. Meanwhile, rapid urbanization and growth in automobile markets have led to massive ground-level air pollution. However, research on how much urban traffic contributes to the ultra-fine particulate is limited. The reason is that the transformation of motor-vehicle emission to ambient air pollution involves complicated chemical processes especially when considering the secondary by-products. In practice, the estimation has yielded a wide range of results. In U.S. cities, the contribution of motor-vehicles ranges from 5% in Pittsburgh, PA to 55% in Los Angeles, CA (Tager et al. (2010)). Zhang et al. (2013)estimate the contribution by traffic and waste incineration at 4%; Lelieveld et al. (2015)estimate that motor-vehicle travel alone contributes 3% in Beijing. However, under different definitions on the toxic level of each pollutant (PM2.5, NO, SO2, O3, etc.), the level of contribution by ground traffic remains uncertain. Our study will contribute to this limited literature by providing an implication on the extent to which the automobile emission accounts for the air pollution.

2.2 Transportation Policies and Subway Expansion

In past decades, the Chinese automobile industry has grown to the largest in the world with a total output of around 29 million units including 24.8 million passenger vehicles in 2017, and the automobile sales has seen a five times growth in the last ten years (Li et al. (2014)). Figure 2 shows the vehicle sales development in China and the U.S. since 2001. In 2001, approximately 0.85 million passenger vehicles were sold in China, while after 2009, China's annual new passenger vehicle sales surpassed the record set by the U.S. and reached a new sales record of around 25 million in 2017.

The Beijing government has taken several measures in order to control the air pollution and the traffic congestion caused by the increasing car ownership. The first measure is the driving restrictions based on the last digit of the license plate. On each weekday, private automobiles with license plates ending with two certain numbers will be restricted from driving during 8am to 8pm. During the 2008 Olympic Games period, also when the air pollution is extremely hazardous, like the "red alert" days, half of the private vehicles are restricted off the road (restriction based on odd and even numbers).[2]The driving restriction does slow down the increasing trend of air pollution significantly, Viard and Fu (2015) find that traffic restriction in Beijing led to a 19% decline of API during every-other-day restriction and a 7% decline during one-day-per-week restriction. This is consistent with the findings of Chen et al. (2013), who examine the effectiveness of different environment measures China government adopted to prepare for the 2008 Olympic Games. Meanwhile, the increasing trend in the automobile ownership has not been slowed down effectively.[3] Figure 2 shows that from 2008 to 2009, the vehicle sales in China sees the largest increases by 49.44%. To deal with the increasing vehicle sales, Beijing government adopted automobile license quota systems in major cities to control the increasing ownership of vehicles. Since 2011, a lottery system was adopted in Beijing for the license plate allocation. The possibility of getting a license plate in Beijing has decreased from 1:10 to 1:100 as the number of licenses allocated is restricted year by year. As shown in Figure 2, the increasing rate has been slowed down after 2011. However, given the large population base and the existing automobile ownership, there will be a lag before the increasing trend of automobile ownership will be affected.

Along with the demand-side (push) strategies, the Beijing municipal government has also been investing heavily in transportation infrastructure such as buses, roads, and subway lines. From a global perspective, Beijing's rapid development of mass transit since 2007 is unprecedented. From 2007 to 2015, the total investment in transportation facilities amounted to over 430 billion Yuan (about USD 67 billion). During this period, 14 new subway lines and one airport expressway were constructed with a total length of 440 kilometers, making the Beijing subway system not only the most rapidly expanded, also the world's longest.[4] Figure 3 shows the Beijing subway expansion timeline. The rapid subway expansion program is still ongoing in Beijing: another 12 subway lines are under construction and scheduled to open before the end of 2020 with a total length of nearly 378 kilometer. Similar large scale

[2]Red alerts are the highest of the four-tiered pollution warning system used by mainland China. 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-hour period.

[3]Davis (2008)studies the effectiveness of driving restriction in Mexico City, however, the results show that the driving restriction in Mexico City does not contribute to improvement in air quality and people tended to buy more cars instead of substituting to low-emissions public transportation; Zhang et al. (2017) find similar results from studying the impact of driving restrictions implemented in Bogotá, Colombia on air pollution.

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

and rapid expansions of subway systems are taking place in other major cities throughout China.

A few studies have looked at the effect of a single transit line on air pollution in other cities of the world. Chen and Whalley (2012) focus on a single subway line in Taipei, and find the opening reduced CO by 5 to 15 percent, but no significant reduction in other major pollutants. Goel and Gupta (2016) examine the causal impact in the context of network extension in Delhi, India and find a strong reduction effect on NO and CO. Similarly, Zheng et al. (2017)focus on the opening of the first subway line in Changsha, China and adopt a similar method to ours. They see a 18% reduction in one key tailpipe pollutant, carbon monoxide (CO) in the areas proximate to subway stations. However, not all studies have found significant evidence of the pollution reduction effect from increase in the public transit supply. Both Beaudoin and Lin-Lawell (2016) and Rivers et al. (2017) find no robust evidence of the pollution reduction effect. Beaudoin and Lin-Lawell (2016) even find a small deterioration in the overall air quality.

The lack of clear evidence could be a reflection of two counteracting facts. First, the subway expansion could lead some commuters to switch from private cars to 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)). In the long run, this traffic creation effect could undo the positive impact realized through the first channel. So the net effects of subway expansion on air quality are ambiguous in theory, especially in the long run.

2.3 Data Description

Our study is based on three major datasets. Table 1 presents the description for the major variables. The first data set contains the daily station-level air pollution measurements from 27 monitors throughout Beijing during 2008 to 2017. We use the station-level daily Air Pollution Index (API) from 1/1/2008 to 12/31/2012, and the station-level daily Air Quality Index (AQI) from 1/1/2013 to 5/12/2017. The API is an index that shows the level of air pollution in this city or area, and is based on five atmospheric pollutants, sulfur dioxide (SO2), nitrogen dioxide (NO2), suspended particulates (PM10), carbon monoxide (CO), and ozone (O3) measured at the monitoring stations throughout each city. The pollutants that Chinese government take into account are the first three. Starting from 2013, the Chinese government replaces API with AQI which considers PM2.5 separately from PM10 as a major pollutant. The API (AQI) level is determined by the highest of the three pollutant scores.

API data from 2000 to 2010 shows that, during the decade, there are 1196 days that the inhalable particulate matter, PM10, is the dominant air pollutant. That is around 96.76% of all air pollution days. The standard of scoring each pollutant for both API and AQI is showed in Table 2.[5]

For Beijing, two types of API (AQI) data are available. One is the aggregate daily API (AQI) released by the Ministry of Environmental Protection (MEP) of China, which combines all monitoring stations in Beijing, and is more easily to be manipulated by the government. The more preferred alternative is the monitoring station-level daily API(AQI) released by the Beijing Municipal Environmental Monitoring Center (MEMC). (Lu (2016)) Also, the 27 monitoring stations located sparsely in both inner Beijing and the suburban counties would provide more spatial variation and reliability. [6]

Atmospheric and geographical literatures studying air pollutants and their potential health effects have widely adopted satellite measurements such as **Aerosol Optical Depth (AOD)**,[7] which researchers are increasingly using in the environmental economics literature (Chen et al. (2013); Gendron-Carrier et al. (2018)). The AOD data are acquired by the Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA's sensor on the Terra and Aqua satellites. The two satellites provide daily measures of AOD at two different resolution levels: 3 by 3 km and 10 by 10 km. For each day, we have four raster files for the AOD data in Beijing. We mosaic the multiple raster files which contain some part or all of the geographical area of Beijing into one raster picture per day and then select the pixels that fall into the city boundary. The final data format we have is daily AQUA AOD at the 10k resolution level (with 432 pixels), daily AQUA at the 3k resolution level (with 4620 pixels), daily TERRA at the 10k resolution level (with 414 pixels), and daily TERRA at 10k resolution level (with 4680 pixels).

A series of papers (Kumar et al. (2011), Gupta et al. (2006), Kumar et al. (2007)) have compared the AOD measurement with the measures of the ground level particulate matters

[5]Suppose in an area, the mean PM_{10} density is 0.215 mg/m^3, the SO_2 density is 0.105 mg/m^3, the NO_2 density is 0.08 mg/m^3. Then the score assigned to PM_{10} is calculated as follows: According to Table 2, the PM_{10} density 0.215 mg/m^3 belongs to 150 $\mu g/m^3$ - 350 $\mu g/m^3$, which is 0.15$mg/m^3 -$ 0.35mg/m^3, according to the correspondent API range 100-200, the PM_{10} score I is: $I = \frac{200-100}{0.350-0.150} \times (0.215 - 0.150) + 100 = 132$. Thus, I=132 ($PM_{10}$); I=76 ($SO_2$), I=50($NO_2$). The area's API for that day is the largest score among all the air pollutants: API $= max(132, 76, 50) = 132$ and the major air pollutant is PM_{10}.

[6]Taking the aggregate API and average of the station-level API from a same period, for example the year of 2009, we found that there are in total 283 days counted as "great" (0-50) or "good" (50-100) using aggregate API. However, when we average the station-level API and evaluate it using the same standard, the days that can be counted as "great" or "good" are only 271 days, which directly shows the government's manipulation on aggregate API data.

[7]AOD is the degree to which aerosols prevent the transmission of light in the atmosphere. Tiny solid and liquid particles suspended in the atmosphere are called aerosols. An aerosol optical thickness of less than 0.1 indicates a crystal-clear sky with maximum visibility, whereas a value of 1 indicates hazy conditions.

(PM2.5 and PM10), and concludes that AOD is a good measure of airborne particulates. Although the coverage of this satellite data is nearly global, there are still many issues which may cause missing data. One reason is that the MODIS is sensitive to cloud coverage, it can only record AOD during cloud-free days, so we see a strong seasonality in the AOD data. In addition, because we are focusing on one city, and the satellites are capturing most but not all areas in the world, some pixels in Beijing are missing too. Our analysis with the satellite data is ongoing, we expect the examinations with the two types of air pollution measurements would serve as robustness checks for each other.

In addition to the air pollution data, this study leverages the spatial variation from the sparsely located air quality monitoring stations and subway stations. Figure 4 shows the distribution of the 27 monitoring monitors, among which eleven are central government operated, and the rest are local government operated. Geographically, eight monitors lie within the 5th ring areas, and the rest are outside 5th ring areas. Between the sample period 2008 to 2016, there are in total 14 new subway lines in Beijing, and the total number of new subway stations is 255. Figure 5 shows the map of Beijing subway stations, most of which are distributed in the inner districts of Beijing to serve the area with the greatest travel demand. [8] Under the special situations such as the subway line extension, or multiple lines at the same opening date,[9] we treat all the stations that are opened on the same day as one opening, regardless of which lines the stations belong. The following analysis is based on the ten opening dates throughout the sample period of 2008 to 2016.[10] [11]

Our density measurement relies heavily on the distances between each monitoring station and each subway station because the monitors at different locations may be affected differently by the openings. Figure 6 shows the relative locations of Beijing air quality monitoring stations and subway stations in 2016. Most of the subway stations are distributed centrally in the city of Beijing. On the other hand, the air quality monitors are distributed sparsely around the entire Beijing area providing some intuitive justification for our alternative DD specifications in which we regard the monitors in the suburbs as the control group for the monitors in the inner city. During the data period of API (2008-2017), the locations of monitors did not change, so the variation in distances comes from the subway expansion

[8] The Beijing government has also developed the public transit for the suburban districts. On Dec 30, 2010, four subway lines targeting on the suburb cities were opened, which were Line Daxing, Changping, Fangshan and Yizhuang.

[9] Note that Line8 and Line10 are opened on the same day. Also, some individual stations which are numbered as a part of Line 8 are opened on the same day with Line 9.

[10] The ten opening dates focused in this study are 2008/7/19, 2009/9/28, 2010/12/30, 2011/12/31, 2012/12/30, 2013/5/5, 2013/12/28, 2014/12/28, 2015/12/26 and 2016/12/31.

[11] Notice that a single station might be opened later than the general opening date of the subway line it belongs to due to unobserved reasons, in this case, we combine those opening days with only one subway stations with the most recent opening date.

only.

The last dataset contains a set of weather variables: average temperature, average relative humidity, precipitation, wind direction, wind speed and dummies for rain, snow, storm, and fog. Wind direction data is hourly and the other weather variables are daily. The weather conditions are essential for our analysis because they have significantly explanatory power for air pollution. We need to further note the construction of wind variables: wind speed and wind direction. Based on the fact that the particulate matters travel quickly with the wind, wind direction and speed are critical to the air pollution. The city Shenyang, for example, northeast of Beijing, is one of the most highly polluted cities in China due to heavy-polluting industries. A strong wind from the northeast will blow the pollutants from Shenyang to Beijing, causing worse air quality. Meanwhile, during the same day, if the wind direction significantly changes and the wind speed increases, the final consequence of the wind transportation of pollutants relies on the aggregation of the wind through the day. Thus, we regard the wind as a vector where the angle represents the direction, and the length represents the speed. This concept is crucial because the wind data is hourly while the other weather data is daily. Thus, directly averaging the hourly direction variable (from 0 to 359) will generate misleading data and neglect the impact of wind speed. We instead use the vector summation to get the daily wind data and then classify it into sixteen directions (categorical).

Table 3 provides a summary statistic for the main weather variables and the wind directions dummies. The mean distance between a monitor to the subway station ranges from 19.41km to 37.23km, with the smallest distance as 0.34km and the largest as 112.54 km. Table 4 summarizes the subway density, the number of new stations and the number of new stations opened in the vicinity of air quality monitors by each opening. The network density for a given location (e.g., an air quality monitoring stations) measures the assessiblity to the subway system and is constructed as a weighted sum of stations with the weight being the inverse squared distance between the location and the subway stations. As the network expands, the measure increases and the change from each new line is affected not only by the number of stations on that line but also the location of the subway stations on that line relative to the monitoring stations.

Table 5 presents the sample averages of log(AQI) 60 days before and after of each new subway line opens. The top panel shows the raw averages while the bottom panel presents the residuals after control for weather conditions and a rich set of time and location fixed effects (the same set of controls to be used in regression analysis). The treatment group is defined as the monitoring stations within 2km of a new subway line while the control group is defined as the monitoring stations more than 20km away from the new subway line. The top panel shows an increase in log(AQI) of 4% on average after a subway line opens. This could be driven by seasonalities: nine of the 14 new lines opened in December and air quality tends to get worse in January and Febrary relative to November and December due to winter heating in Beijing. The bottom panel shows an average 4.6% reduction in AQI after a new subway line opens.

Figure 7 depicts the daily changes of log(AQI) 60 days before and after each new subway line opens for the treatment and control groups separately after control for weather conditions and a rich set of time and location fixed effects. The treatment group appears to have a higher AQI than the control group (relative to their respective baseline levels) one month before the new lines open but have a lower AQI about 20 days after the opening. The difference seems to increase overtime after the openning while the treatment group exhibit a lower AQI. During the month before the opening and the 20 days after the opening, there does not seem to be significant differences between the two groups.

3 Empirical Strategy

In this section, we discuss the empirical models and the identification challenges. The main empirical strategy is based on the instrumental variable approach to address the concern about endogenous subway locations. We then present the alternative Differece in Differences strategies and the heterogenous treatment effect analysis.

3.1 Instrumental Variable Strategy

In order to continuously measure the subway expansion, we define an aggregate weighted subway density measure. This density measure includes the distances from monitors to subway stations as inverse weights for the number of subway stations since the closer the subway stations are located, the more easily people may access them, and consequently they will obtain larger benefits. Our OLS estimation (shown in Eq 1) based on the aggregate subway density implies the assumption that there is no selection bias in locations of subway stations within each subway line.

$$ln\ AQI_{it} = \alpha + \beta \text{Density}_{it} + \mathbf{X}_t\gamma + \kappa_i t + \tau_t + c_i + \varepsilon_{it} \tag{1}$$

$$\text{where Density}_{it} = \sum_i \frac{1}{d_{ijt}^2} \tag{2}$$

The outcome variable is $ln\ Y_{it}$, which is the logarithm of Air Pollution Index (API) for 2008-2012 and Air Quality Index (AQI) since 2013 measured by monitor i at time t

where $i = 1, \ldots, 27$, and $t \in [2008/1/1,\ 2017/12/31]$. The key explanatory variable is Density_{it}, which measures the inverse squared distance weighted sum of subway stations opened at time t for each monitor i. The density is then aggregated to count for the subway stations previously opened. $\mathbf{X}_t$ includes a rich set of controls: weather variables, such as average temperature (C°), relative humidity (%), wind speed (m/s), rainfall/snowmelt (mm), dummies for rain, snow, storm, and fog and 16 wind direction dummies. To control for the other confounding factors that may vary across time but are not well controlled by the time fixed effects, we include a monitor specific time trend in our model indicated by $\kappa_i t$ to allow the unobserved trend to vary across both time and monitors. The model also includes five indicators for each pair of numbers that are restricted at time t as he last digit of license plates since it directly correlates with the daily traffic volume. ε_{it} is the unobserved, time-varying and monitor specific shocks. The time-invariant, monitor-specific variation, such as location attributes that affect air quality, is controlled by the monitor fixed effect (FE) s_i. τ_t is the set of temporal fixed effects which includes Year FE, Season FE, Day of Week FE and Holidays FE. Additionally, to allow for the correlation across monitoring stations in one day, we estimate with robust errors, clustered by each day.

Given that the subway system is designed to serve the areas with the highest travel demands, many may have concerns about this strong assumption. Even though we have controlled for the location specific time trend, there may still exists endogeneity caused by the omitted factors correlated with air pollution which the planners take into consideration when designing the subway network but are unobservable to econometricians. For instance, if the planners predict the future air pollution level of different areas and intentionally place the subway stations to areas with the most severe air pollution or traffic congestion issues, the density measures would be endogenous.

To address the concern of endogenous selection of subway stations locations, we construct a hypothetical subway network to instrument for the density measure which is a function of subway locations. The hypothetical network is a minimum spanning tree (MST) following the approach in the recent literature on the economic impacts of road infrastructure investment (Banerjee et al. (2012), Michaels (2008), Faber (2014), Morten and Oliveira (2016)). We use the original subway plans as a reference and generate a hypothetical subway network to serve all districts of Beijing (both central and suburban) as the sole policy objective. Figure 8depicts the hypothetical subway network where we straighten up all the subway lines and reallocate the observed subway stations to the nearest location on the hypothetical lines.

The hypothetical subway network satisfies the relevant assumption of a valid instrumental variable because it is based on the original subway plan. It has the same number of stations, and the same level of connectivity in terms of the number of transferring stations as the current subway system. And the exogenous restriction is satisfied by design because the hypothetical subway map is solely built on the coverage and connectivity objectives. It should not be correlated with the unobserved factors for which planners endogenously select the subway locations to meet their expectations on future air pollution levels.

The advantages of the IV strategy using a continuous density measure is its flexibility. The estimation results can be applied to any locations of Beijing as long as the geographical information is available. Using the popular transportation analysis areas: Traffic Analysis Zone (TAZ), we could measure the distance from the center of each TAZ and each subway station to get the subway density of each TAZ center. Then we are able to apply the estimation results to finer areas of Beijing and evaluate the different levels of environmental benefits by each phase of subway expansion.

3.2 Alternative Specifications: Difference-in-Differences

In addition to the IV strategy with continuous measures of density, we propose an alternative Difference in Differences (DD) strategy as a robustness check and estimate the heterogeneity of the impact. Intuitively, one may regard the air quality monitors as the location of representative households. The closer the monitor is located to the new subway line, the easier travelers can access it. Consequently these travelers are more likely to switch their travel mode from driving to taking subway which in turn affects air quality. Using this idea of accessibility, we define the treated monitors as the monitors that are located within a 2km radius of the new subway line and the untreated monitors as those that are further than 20km. We treat the area in between as the buffer zone and drop the monitors in the buffer zone throughout the analysis to address the concern of misclassifying treatment status.

The basic Difference-in-Differences framework is defined as

$$lnY_{it} = \beta Treated_{it} \times Open_t + \mathbf{X}_t\gamma + \kappa_i t + \tau_t + c_i + \varepsilon_{it} \tag{3}$$

Treated$_{it}$ is a treatment indicator that takes a value of one if monitor i is within 2km of the new subway lines at time t. Since the subway lines are designed to serve different areas of Beijing, the set of treated and control monitors vary across different openings. According to the subway expansion timeline, on average there is one new subway line opened in each year between 2008 to 2016. We choose the time window 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. We use $Open_t$ to indicate the time window which equals to one for dates fall into 60 days before and after each opening date. The parameter of interest in the DD specification is β, which captures the short-term negative causal impacts of subway opening on air pollution for areas in the vicinity of the new subway stations.

The key assumption of DD is that in the absence of subway opening, air quality in the treatment and control group would follow similar trends. Thus, we need to test the validity of the parallel trend assumption for air pollution before openings. To do so we divide the 60-day time window around opening dates into twelve 10-day intervals with six pre-opening periods ($n < 0$) and six post-opening periods ($n > 0$). We run the following regression to test the trend of API for different groups and drop one of the pre-opening intervals to avoid multicollinearity

$$ln\ AQI_{it} = \alpha + \sum_{n=-6}^{6} \beta_n \phi(n) \times \text{Treated}_{it} + \mathbf{X}_t\gamma + \kappa_i t + \tau_t + c_i + \varepsilon_{it} \tag{4}$$

Coefficients β_n are presented in Table 8. The test on pre-treatment trends between the two groups reveals no statistically and economically significant difference. According to Table 8, the estimated coefficients in the pre-opening periods are insignificant, which shows that the air pollution trends in the treated group (within 2km) and the control group (outside 20km) are similar in the days before opening. This provides some support for the common trend assumption in the absence of subway opening.

There are other identification concerns that we want to discuss further. The first concern is the pollution caused by constructions before subway line opens. 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 pollution does exist, then the estimation results will be overestimated. The air pollution index during days before opening will be higher than if there is no subway construction, thus the air pollution problem will be relieved once the construction ends even in absence of any subway openings. However, based on the safety regulation of subway systems, one should not worry about the overestimation issue caused by the ground construction. According to national standards of subway construction in China, every subway line must operate under both trial running and trial operation before the official opening date. The trail running is over a three-month period during which the subway train will be tested without any passengers after the ground work finished completely. [12] Since our focusing sample period is the 60-day window around opening dates, we do not expect the impact of construction pollution.

The second identification concern might arise from endogenous locations of the subway stations based on expectations of future traffic congestion and air quality in different areas.

[12] The trial operation period is the last 20 days of the trail running process, during which the subway with passengers (but not to the public) will be tested following the scheduled time and route.

For example, endogenous selection of subway locations in regions with faster future growth in travel demand and deterioration in air quality would lead to an underestimation of the true causal impact. To address this concern, we control for monitor specific time trends. A similar concern lies on the endogenously selected opening dates with the anticipation of better air quality after opening. Based on the nature of the subway planning process in Beijing, we argue that this concern is unlikely to affect our estimation because a new subway line takes years from planning to operation. The only possibility is that the local government selects the national holidays as the opening dates or the last few days of a year for specific political purposes. To address this issue, we control for all the holidays and the policy on national working schedules.

Rationale behind the choice of treatment group (2km) – The variation in the subway ridership will rely on the group of passengers who live near the new subway line. Thus, the radius of the area that a subway station can be easily accessed is crucial to our research. A typical length of time that people would like to travel to a subway or bus station is about 5-15 minutes, according to the survey and literature about the accessibility of public infrastructure. The average walking distance, based on an average walking speed of 5km/h, is less than 1km. Besides walking, another frequently used travel mode that people choose to commute between residences and public transportation stations in China is biking, especially in recent years when the bike sharing programs became popular. Based on an average biking speed of 18km/h, the average travel distance within 5 to 15 minutes is about 3km. Because the average travel distance considering both types of commuters is around 2km, we choose 2km as the dividing point.

Buffer Zone – We set the area between 2km to 20km away from the subway lines as the buffer zone and only use the monitors outside the buffer zone as the control group to avoid spatial correlations of the economic activities in the neighborhood. Since the transportation system is a network system, for both ground transportation and underground rail transit, the monitors that are just a little further away might also capture the impact of subway opening on the traffic volume. Thus, the monitors located in the buffer zone may not serve as valid counterfactuals for the treated monitors. Even though our choice of treatment and control groups passes the pre-treatment common trend test, there may still exist concerns about the spillover effect.

One may be concerned that if the drivers anticipate the congestion caused by the new subway stations and choose to avoid the vincinity area, the traffic will be largely diverted into the buffer zone. Thus, the pollution reduction effect of subway expansion using the DD framework may be overestimated when the buffer zone is dropped in the estimation. This is a reasonable concern considering that the road transportation is a network system, so the traffic diversion of subway opening can potentially affect the entire city. This concern can be well addressed by the continuous density specifications mentioned above. Comparing to the DD framwork, the density measure relaxes the assumption of the spillover effect, and provides an esimates for the city-wide effect of subway expansion in the long term. It also better addresses the endogeneous subway locations issue with the hypothetical subway density as an instrument. Additionally, the density measure is more flexible in terms of future predictions for subway lines that are planned already but not yet opened. Although the DD framework needs stronger assumptions, it has advantages in evaluating the hetorogenous impact over time and across space.

To examine the heterogeneity we evaluate the next three specifications. First, we would like to see when exactly does the subway opening effectively reduce the air pollution and how does the effect vary across different time windows. We run the DD regression with the full set of controls under multiple time windows. We examine the temporal pattern of the effect. The element equals to 0 for days before opening and takes the values $1, 2, 3, ..., T$ for each day after opening. The monitors are still classified as the same two groups as before. According to our assumption, the effect on air pollution will happen along with the change in commuters' travel behaviors, so we would not expect a sharp drop in air pollution since people need a short period to adjust their travel mode to the new choice set. Additionally, since we restrict the time window to 60 days after opening, the reduction effect should maintain a constant level or present an upward trend over the 60 days post opening.

To adapt the idea of accessibility to the DD estimation, we interact the time window with the number of new subway stations within the vicinity of the treated monitors. Equation 5 represents this specification with the same control group, buffer zone and time window as the basic DD specification.

$$\begin{aligned} &ln\ AQI_{it} = \alpha + \beta \mathrm{N}_{it} \times Open_t + \mathbf{X}_t \gamma + \kappa_i t + \tau_t + c_i + \varepsilon_{it} \\ &\text{where } N_{it} = \sum_j \mathbf{1}(\mathrm{Dist}_{ijt} \leq 2\mathrm{km}) \end{aligned} \tag{5}$$

The baseline assumption is that there exists heterogenous treatment effect for the treated monitors with different accessibility to the new subway line. The more new stations located nearby, the larger the pollution reduction effect the treated monitor would be benefit from.

4 Empirical Results

In this section, we first present the regression results for the empirical specifications mentioned in the last section and then discuss on the policy implementations.

4.1 Regression Results

Table 6 shows the results from the OLS estimates using continuous density measures as in Equation 1 for specifications with different sets of control variables. From the first to the last column, we add the control variables successively. Without any control we see that the increase in density results in an increase of air pollution, which is biased mainly by the location specific factors. From the map of the 27 monitors, we see that the monitors are located in different districts of Beijing with different the population density, economic structure and traffic density. As we include the monitor FE, the effect of increasing subway density on air pollution becomes negative and robust. As the monitor specific time trend is included, the magnitude of pollution reduction effect becomes larger. One standard deviation increase in subway density reduces the air pollution by 1.4%. The summary of density changes by each opening is shown in Table 4. Taking Line 6 which is opened at Dec 30, 2012 as an example, the density increases by 17.44 (around 5 sd) which leads to a 6.9% decrease in air pollution.

The IV 2SLS estimation result is shown in Table 7, where both the first and the second stage are reported. From the first stage F-statistics, we see that the IV density measure based on the hypothetical subway network we construct is highly relevant to the endogenous density measure and the second stage estimation is consistent with the OLS estimates but with a higher magnitude. This shows that there does exist an underestimation issue in terms of the magnitude of the pollution reduction effect. With the IV, one standard deviation increase in the subway density will contribute to a 2% improvement in air quality. Using the same example as above, the opening of Line 6 improves air quality by 10%.

A similar pattern of including different set of controls is found in Table 9, which presents the results from the basic DD model (Equation (3)) Without any control, the unconditional difference between the treated and control group in is positive and significant. As we include the monitor FE, the effect of subway opening on the nearby air pollution becomes negative and robust to model specifications with monitor specific time trend. The magnitude of the short term difference is also relatively stable with different specifications, which is around -7.5%. This result shows that within a 60-day time window around a subway line's opening, the monitors in the vicinity (within 2km) of subway stations will exhibit a 7.5% reduction in AQI compared to the monitors that are not influenced (outside 20km in this scenario).

In the following tables, we only report the results from the model specifications with the monitor FE included and its interaction with driving regulation and time trends successively to show the robustness of the estimations.

Table 10 compares different time windows under the same specification as Equation (3). From column (1) to (7) the time window increases by ten days consecutively. The sign of the interested estimator is robust under all the time windows. However, the first two time windows fail to provide significant estimations. The effect is the largest during the 60-day window and becomes slightly less after that. The difference in magnitudes of the following four specifications is not economically significant. This suggests that the pollution reduction effect of subway opening is robust to the choice of the time window that is longer than 30 days. The insignificance from the specifications with the short time-window is likely driven by the fact that it takes time for commuters to adjust for the new travel option. Table 11 shows the effect under a continuous measure of the time variables. Within the 60-day time window, the pollution reduction effect of subway opening increases at a rate of 0.3% per day, consistent with the result from Table 10.

Table 12 presents the specification taking into consideration the accessibility to the subway lines. The result shows that one additional subway station added to the vicinity of a monitor reduces air pollution significantly by 2.1% to 3.1% within the 60-day window. The result is significant both statistically and economically and consistent with the IV estimation resutls. Table 4 contains the summary of the number of new subway stations that are opened near the monitors. Taking the same example Line 6 as above, its opening brings five closed by subway stations to treated monitors and improves air quality by 10% to 15%. Given that we have not considered the type of subway stations in the regression, we expect this estimation of the number of new subway stations to be the lower bound of the actual effect. If one or more new subway station located within 2km is a transferring station, then the accessibility to the subway will be significantly improved which should result in further reduction in the traffic-originated air pollution.

4.2 Benefit-Cost Analysis

This section presents a back-of-the-envelop analysis on the benefit of subway expansion from 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 by commuters.

Our empirical analysis finds that subway expansion leads to significant improvement in air quality. Table 13 shows the estimated air quality improvement due to each subway line based on the benchmark specification (IV results in Table 7). The air quality improvement ranges from 0.69% by line 16 opened on 12/31/2016 to 10.46% by line 6 opened on 12/30/2012. Recent literaure from both epidemiology and economics has shown 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);Currie and Walker (2011); Knittel et al. (2015); Greenstone and Hanna; He et al.; Ebenstein et al.).

To calculate the mortality impact, we take the estimates from Ebenstein et al. (2017) which study the impact of long-term exposure to airborne particulate matter on mortality using a regression discontinuity design. They find that a 10-$\mu g/m^3$ increase in PM_{10} increases cardiorespiretory mortality by 8% and the impact varies across age cohorts by not across gender. Following the analysis in Barwick et al. (2017) to montetize the mortality impact, the mortality cost amounts to \$13.38 billion across Chinese population from a 10-$\mu g/m^3$ increase in PM_{10}, or \$64.9 per household in Beijing when adjusted for the Beijing per capital income (in 2015 dollars). The morbidity cost of air pollution comes from Barwick et al. (2017) which provides the first comprehensive anlaysis of the morbidilty cost in China based on the universe of credit and debit card spending. They find that the morbidity cost from a 10-$\mu g/m^3$ increase in $PM_{2.5}$ is \$20.2 (in 2015 dollars) per household.

The congestion relief benefit comes from the value of the saved commuting time. Using a regression discontinity design, Yang et al. (2018) estimate that each new subway line reduces travel delay by 15% on average based on the subway lines opened between 2009 to 2015. The Beijing Annual Transportation Report shows that the average traffic delay time is around 20 mins per hour. We assume that the delay occurs during the peak hours (7am-9am and 5pm-7pm) during the weekdays 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)), or 62.98 Yuan per hour (\$9.5 per hour) based on the monthly wage of 10,077 Yuan.

Table 14 presents the cost-benefit calculations during a 10-year period after each subway line opened. The cost includes both the upfront construction cost and the operating cost. We discount the operating cost and the benefit at a 5% 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 \$24.4 billion or 43.3% of the total cost while the benefit from congestion relief is \$26.9 billion or 48% of the total cost. Table 15 presents the cost-benefit calculations during a 20-year period where the benefit from health and congestion relief accounts for 52.8% and 58% of the total cost respectively. The analysis suggests that the health benefit from improved air quality is a substantial portion of the overall benefit of subway expansion.

Our benefit estimates are conservative for the following three reasons. First, the mortality benefit is based on the value of a statistical life of $2.27 million (in 2015) from Ashenfelter and Greenstone (2004), rather than the central estimate of $8.7 million figure recommended by U.S. EPA. Second, the value of time is assumed to be 50% of the wage, rather than 100% of the hourly wage (Small (2012); Wolff (2014)). Third, the benefit calculation neither include the benefit from improved reliability in commuting nor the benefit from a larger choice set of travel modes (Small et al. (2005)). Nevertheless, our analysis suggest that the benefit of subway expansion would exceed the cost within 20 years of the operation even based on conservative benefit estimates.

5 Conclusion

To address worsening air pollution and traffic congestion acorss urban areas in China, central and local governments in China 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 4% of its GDP. Beijing has been leading the way among major cities in public transportation infrastructure by rapidly expanding 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 on the impact of subway expansion on air quality. By leveraging fine-scale air pollution data and the rapid rollout of 16 new lines from 2008 to 2016 in Beijing, we find that the opening of new subway stations improves air quality significantly from a variety of empirical specifications. The IV analysis based on the network density measure shows that one standard-deviation increase in the density improves air quality by 2% in the long term. Similarly, the distance-based difference-in-differences framework finds that air quality improves by 2.5% in the vicinity (within 2km) of a new subway station within a 60-day window after each new subway station opens. The 10-year total discounted health benefits of the subway expansion amounts to $24.4 billion due to reduced mortality and morbidity from improved air quality, accounting for 43.3% of the total cost including both the construction and operating cost.

By quantifying an important benefit of subway expansion, this study should help urban planners make better-informed decisions on subway investment. Future research could try to understand the underlying mechanisms of pollution impact by studying how subway expansion affects commuters' travel behavior and travel mode choices. This could allow us to tease out the Morhing effect and the induced demand effect. In addition, it would be interesting to further examine the impact of subway expansion on the location choices of households and firms, which could affect the long-run outcomes of traffic congestion and air pollution.

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Table 1: Variable Descriptions

Variable	Unit	Definition
Air Pollutants		
AQI	*index*	Air quality index ranging from 0 to 500, defined as "excelent" if $0 \leq AQI \leq 50$; "good" if $50 < AQI \leq 100$; "slightly polluted" if $100 < AQI \leq 200$; "moderately polluted" if $200 < AQI \leq 300$; "severely polluted" if $300 < AQI \leq 500$.
API	*index*	Air pollution index ranging from 0 to 500, defined as "excelent" if $0 \leq API \leq 50$; "good" if $50 < API \leq 100$; "slightly polluted" if $100 < API \leq 200$; "moderately polluted" if $200 < API \leq 300$; "severely polluted" if $300 < API \leq 500$.
Treatment		
$\mathbf{1}(Open) \times \mathbf{1}(Distance \leq 2)$	dummy	30/60 days after a subway station open within 2km distance from an air pollution monitoring station
Weather Variables (Daily)		
Average temperature	^oC	Mean daily temperature (the average temperature in each 24 hour period).
Maximum temperature	^oC	Maximum daily temperature (the max temperature in each 24 hour period).
Minimum temperature	^oC	Minimum daily temperature (the min temperature in each 24 hour period).
Average sea level pressure	hPa	Mean daily atmospheric pressure at sea level at a given location (the average sea-level pressure in each 24 hour period).
Average relative humidity	%	Mean daily relative humidity (the average relative humidity in each 24 hour period).
Total rainfall/snowmelt	mm	Total daily percipitation (the total percipitation in each 24 hour period).
Average visibility	km	Mean daily visibility (the average visibility in each 24 hour period).
Average wind speed	km/h	Mean daily wind speed (the average wind speed in each 24 hour period).
Max sustained wind speed	km/h	Maximum sutained wind speed (the max sustained wind speed in each 24 hour period).
Maximum wind speed	km/h	Maximum wind speed (the max sustained wind speed in each 24 hour period).
Rain	dummy	Rain dummy: 1 if there was rain or drizzle , 0 otherwise.
Snow	dummy	Snow dummy: 1 if there was snow , 0 otherwise.
Storm	dummy	Storm dummy: 1 if there was storm , 0 otherwise.
Fog	dummy	Fog dummy: 1 if there was fog , 0 otherwise.

Table 2: Transformation from Pollutant Concentrations to API and AQI

API	**PM10**($\mu g/m^3$)	**PM2.5**($\mu g/m^3$)	**O3**($\mu g/m^3$)	**NO2**($\mu g/m^3$)	**SO2**($\mu g/m^3$)
0-50	0-50			0-80	0-50
50-100	50-150			80-120	50-150
100-200	150-350			120-280	150-800
200-300	350-420			280-565	800-1600
300-400	420-500			565-750	1600-2100
400-500	500-600			750-940	2100-2620
AQI	**PM10**($\mu g/m^3$)	**PM2.5**($\mu g/m^3$)	**O3**($\mu g/m^3$)	**NO2**($\mu g/m^3$)	**SO2**($\mu g/m^3$)
0-50	0-50	0-35	0-100	0-40	0-50
50-100	50-150	35-75	100-160	40-80	50-150
101-150	150-250	75-115	160-215	80-180	150-475
151-200	250-350	115-150	215-265	180-280	475-800
201-300	350-420	150-250	265-800	280-565	800-1600
$>$300	$>$420	$>$250	$>$800	$>$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 PM2.5 separately from PM10 as a major pollutant, and also Ozone.

Table 3: Summary Statistics

Main variables	Mean	S.D.	Min	Max	N
Air Pollution Variable					
Air Quality Index	104.91	70.21	5.00	500.00	104042
Distance					
Jul 19, 2008	27.43	22.62	0.69	78.29	837
Sep 28, 2008	30.94	28.03	1.35	99.65	675
Dec 30, 2010	19.41	17.96	0.34	68.85	1026
Dec31, 2010	19.41	17.98	0.34	68.85	297
Dec31, 2011	24.24	18.13	0.64	69.31	513
Oct 21, 2012	27.58	27.51	0.34	90.63	27
Dec 30, 2012	27.58	27.00	0.34	90.63	1215
May 05, 2013	37.23	32.21	1.20	112.54	243
Dec 21, 2013	28.42	24.66	1.01	87.11	27
Dec 28, 2013	28.42	24.29	1.01	87.11	135
Feb 15, 2014	28.42	24.66	1.01	87.11	27
Dec 28, 2014	27.28	24.78	0.94	84.62	1134
Dec 26, 2015	25.50	22.01	3.09	81.65	405
Dec 31, 2016	29.92	22.89	1.49	87.08	270
Total	25.57	24.19	0.34	112.54	9342
Weather Variables					
Air temperature (^oC)	12.97	11.39	-15.04	33.05	3533
Wind speed (m/s)	1.97	1.58	0.02	10.21	3533
Visibility (km)	10.44	5.63	0.63	30.00	3533
Relative humidity (%)	54.64	20.20	6.97	97.83	3533
Weather direction dummies					
Wind direction (*cat.*)	7.95	4.94	1.00	16.00	3533
N =1	0.09	0.28	0.00	1.00	3533
NNE =2	0.09	0.28	0.00	1.00	3533
NE =3	0.06	0.23	0.00	1.00	3533
ENE =4	0.06	0.23	0.00	1.00	3533
E =5	0.06	0.23	0.00	1.00	3533
ESE =6	0.08	0.28	0.00	1.00	3533
SE =7	0.11	0.31	0.00	1.00	3533
SSE =8	0.09	0.29	0.00	1.00	3533
S =9	0.05	0.22	0.00	1.00	3533
SSW =10	0.03	0.17	0.00	1.00	3533
SW =11	0.02	0.12	0.00	1.00	3533
WSW =12	0.02	0.13	0.00	1.00	3533
W =13	0.02	0.12	0.00	1.00	3533
WNW =14	0.04	0.20	0.00	1.00	3533
NW =15	0.11	0.31	0.00	1.00	3533
NNW =16	0.10	0.29	0.00	1.00	3533

Note: The Air Quality Index panel summarizes the daily Air Pollution Index from 2008-2012 and Air Quality Index since 2013 from 27 air quality monitors in Beijing. The distance panel summarizes the distances between 27 monitors and the new subway stations of each opening. The weather panel summarizes the daily, city-level weather conditions.

Table 4: Beijing Subway Expansion and Network Density

Opening Date	Network Density	Change in Density	# of New Stations	# of New Stations within 2km	# of New Stations within 5km
Before 2008	26.56	-	93	19	88
Jul 19, 2008	37.59	11.03	30	8	28
Sep 28, 2009	43.90	6.30	25	5	27
Dec 30, 2010	55.75	11.85	49	2	11
Dec 31, 2011	60.82	5.08	19	2	10
Dec 30, 2012	78.27	17.44	46	5	29
May 5, 2013	80.24	1.98	9	1	5
Dec 28, 2013	82.09	1.85	7	1	4
Dec 28, 2014	90.15	8.05	42	5	23
Dec 26, 2015	91.82	1.68	15	0	10
Dec 31, 2016	92.97	1.15	10	1	3

Note: There were 93 stations before our data period. 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 density and the number of new subway stations within 2km (5km) are the summation based on the locations of 27 air quality monitors in Beijing.

Table 5: Changes in Air Quality Index Before and After New Lines (%)

ln(AQI)	Before	After	△	△△
Control	4.428 (0.008)	4.437 (0.008)	0.009 (0.011)	
Treated	4.483 (0.018)	4.535 (0.022)	0.052 (0.028)	0.043 (0.031)

Residualized ln(AQI)	Before	After	△	△△
Control	0.005 (0.005)	-0.004 (0.005)	-0.009 (0.007)	
Treated	0.022 (0.014)	-0.033 (0.015)	-0.055 (0.021)	-0.046 (0.022)

Note: The top panel shows the sample mean of log(air quality index) 60 days before and after each subway line opens; The bottom panel shows the sample means of residualized log(air quality index) after 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 2km of a new subway line while the control group is defined as the monitoring stations more than 20km away from the new subway line. The standard errors are in parentheses.

Table 6: OLS: The Impact of Subway Expansion on log(AQI) Based on Network Density

	Dependent variable: ln AQI					
	(1)	(2)	(3)	(4)	(5)	(6)
Network Density	0.079***	0.076***	0.049***	−0.006***	−0.007***	−0.014***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
Temperature ^0C		−0.006***	0.006***	0.006***	0.006***	0.006***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Relative humidity (%)		0.004***	0.009***	0.009***	0.009***	0.009***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rainfall/snow (mm)		−0.003**	−0.002*	−0.002*	−0.002*	−0.002*
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Wind speed (m/s)		−0.071**	−0.071**	−0.071**	−0.072**	−0.071**
		(0.033)	(0.031)	(0.031)	(0.031)	(0.031)
Constant	4.377***	4.236***	4.027***	4.085***	4.086***	4.057***
	(0.010)	(0.072)	(0.073)	(0.074)	(0.079)	(0.080)
Wind directions	N	Y	Y	Y	Y	Y
Wind speed * Wind dir.	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
Station FE	N	N	N	Y	Y	Y
Station FE*Tailno	N	N	N	N	Y	Y
Time trend	N	N	N	N	N	Y
Trend*Station FE	N	N	N	N	N	Y
N	91594	86758	86758	86758	86758	86758
R^2	0.02	0.23	0.35	0.39	0.39	0.40
F	982.48	49.54	77.61	96.57	40.07	43.59

Note: Each column reports results from an OLS regression where the dependent variable is log AQI and the key explanatory variable is the standardized network density. 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 station-day. The weather control 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 day-of-week, month-of-year, holiday-of-sample dummies. Spatial fixed effects include dummies for air pollution monitoring stations . Parentheses contain standard errors clustered at date level. Significance: *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

Table 7: IV: The Impact of Subway Expansion on log(AQI) Based on Network Density

	(1) OLS	(2) 2SLS
Dependent: log(AQI)		
Density	-0.0140***	-0.0196***
	(0.00348)	(0.00519)
Constant	4.057***	4.059***
	(0.0801)	(0.0800)
Observations	86,758	86,758
R-squared	0.396	0.396
First Stage:		
Hypothetical Density	0.870***	
	(0.00603)	
IV F-stat	20790	

Note: The Top panel compares the environmental effect of subway expansion from OLS with the estimates from IV. The first column reports results from an OLS regression where the dependent variable is log AQI and the key explanatory variable is the standardized network density. 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 second column reports the result from IV regression.The bottom panel reports the first stage result from IV. The instrumet is the hypothetical subway density from a minimum spanning tree subway network. The unit of observation is station-day.

All three columns control for weather conditions, monitor fixed effects, time fixed effects: year, season, day of week and holiday, and monitor-specific time trends. Parentheses contain standard errors clustered at date level. Significance: *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

Table 8: Pre-treatment Common Trend Test

	Dependent variable: ln AQI		
	(1)	(2)	(3)
≤2km × (0,10] pre-open	0.060	0.066	0.083
	(0.070)	(0.072)	(0.072)
≤2km × (10,20] pre-open	−0.050	−0.042	0.002
	(0.064)	(0.065)	(0.067)
≤2km × (20,30] pre-open	0.088	0.099	0.122
	(0.075)	(0.078)	(0.082)
≤2km × (30,40] pre-open	0.066	0.073	0.071
	(0.076)	(0.078)	(0.086)
≤2km × (40,50] pre-open	−0.120*	−0.102	−0.109
	(0.072)	(0.074)	(0.078)
Temperature ^0C	0.010***	0.010***	0.013***
	(0.003)	(0.003)	(0.003)
Relative humididy (%)	0.015***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)
Rainfall/snowmelt (mm)	−0.006*	−0.007*	−0.006
	(0.004)	(0.004)	(0.004)
Wind speed (m/s)	−0.090**	−0.090**	−0.087**
	(0.038)	(0.038)	(0.037)
Constant	3.776***	3.896***	3.827***
	(0.142)	(0.156)	(0.156)
Wind directions	Y	Y	Y
Wind speed * Wind dir.	Y	Y	Y
Year FE	Y	Y	Y
Season FE	Y	Y	Y
Day of Week FE	Y	Y	Y
Station FE	Y	Y	Y
Station FE*Tailno	N	Y	Y
Time trend	N	N	Y
Time trend * Station FE	N	N	Y
N	17282	17282	17282
R^2	0.52	0.52	0.53
F	43.80	23.18	24.33

Note: Each column reports results from an OLS regression where the dependent variable is log AQI 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 2km from the monitoring station). The control group is the monitors outside 20km. The unit of observation is station-day. The weather control 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 day-of-week, month-of-year, holiday-of-sample dummies. Spatial fixed effects include dummies for air pollution monitoring stations . Parentheses contain standard errors clustered at date level. Significance: *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

Table 9: DD Estimates using log AQI with a Fixed Time Window

	Dependent variable: $\ln AQI$, Time Window: 60-Day					
	(1)	(2)	(3)	(4)	(5)	(6)
1(Open)1(Dist.≤2km)	0.099***	0.073***	0.101***	−0.075***	−0.077***	−0.075***
	(0.027)	(0.021)	(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)
Rainfall/snowmelt (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)		−0.079*	−0.105***	−0.105***	−0.106***	−0.103***
		(0.042)	(0.034)	(0.034)	(0.034)	(0.034)
Constant	4.436***	4.145***	3.725***	3.845***	3.853***	3.762***
	(0.018)	(0.104)	(0.140)	(0.141)	(0.153)	(0.153)
Wind directions	N	Y	Y	Y	Y	Y
Wind speed * Wind dir.	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
Station FE	N	N	N	Y	Y	Y
Station FE*Tailno	N	N	N	N	Y	Y
Time trend	N	N	N	N	N	Y
Time trend * Station FE	N	N	N	N	N	Y
N	18212	17230	17230	17230	17230	17230
R^2	0.00	0.29	0.45	0.53	0.53	0.54
F	13.61	17.51	25.81	47.88	22.80	24.67

Note: Each column reports results from an OLS regression where the dependent variable is log AQI and the key explanatory variable is the treatment indicator (the interaction of number of days after an opening and the treated group indicator). The treatment group is defined as the monitoring stations within 2km of a new subway line while the control group is defined as the monitoring stations more than 20km away from the new subway line. The unit of observation is station-day. The weather control 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 day-of-week, month-of-year, holiday-of-sample dummies. Spatial fixed effects include dummies for air pollution monitoring stations . Parentheses contain standard errors clustered at date level. Significance: $*p < 0.1$, $**p < 0.05$, and $***p < 0.01$.

Table 10: DD Estimates using log AQI with Varying Time Windows

	Dependent variable: ln AQI						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Time Window	10-Day	20-Day	30-Day	40-Day	50-Day	60-Day	70-Day
1(Open)1(Dist.≤2km)	−0.047	−0.040	−0.055***	−0.074***	−0.073***	−0.075***	−0.075***
	(0.037)	(0.025)	(0.021)	(0.020)	(0.019)	(0.018)	(0.018)
Temperature ^0C	0.051***	0.035***	0.027***	0.023***	0.018***	0.012***	0.012***
	(0.009)	(0.006)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)
Relative humididy (%)	0.021***	0.023***	0.020***	0.016***	0.016***	0.015***	0.015***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rainfall/snowmelt (mm)	0.010	0.000	−0.005	−0.008	−0.009*	−0.006	−0.006
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Wind speed (m/s)	0.037	−0.017	−0.087*	−0.139***	−0.113***	−0.103***	−0.103***
	(0.073)	(0.077)	(0.051)	(0.034)	(0.035)	(0.034)	(0.034)
Constant	1.513	2.527***	3.011***	3.378***	3.421***	3.762***	3.762***
	(1.065)	(0.240)	(0.187)	(0.156)	(0.143)	(0.153)	(0.153)
Wind directions	Y	Y	Y	Y	Y	Y	Y
Wind speed * Wind dir.	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Season FE	Y	Y	Y	Y	Y	Y	Y
Day of Week FE	Y	Y	Y	Y	Y	Y	Y
Station FE	Y	Y	Y	Y	Y	Y	Y
Station FE*Tailno	Y	Y	Y	Y	Y	Y	Y
Time trend	Y	Y	Y	Y	Y	Y	Y
Time trend * Station FE	Y	Y	Y	Y	Y	Y	Y
N	3004	5835	8693	11562	14395	17230	17230
R^2	0.73	0.68	0.64	0.59	0.57	0.54	0.54
F	.	35.54	26.75	24.91	24.43	24.67	24.67

Note: Each column reports results from an OLS regression using different time windows (Left to right: 10, 20,... 70-day) where the dependent variable is log AQI and the key explanatory variable is the treatment indicator (the interaction of the time window dummy and the treated group indicator). The treatment group is defined as the monitoring stations within 2km of a new subway line while the control group is defined as the monitoring stations more than 20km away from the new subway line. The unit of observation is station-day. The weather control 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 day-of-week, month-of-year, holiday-of-sample dummies. Spatial fixed effects include dummies for air pollution monitoring stations . Parentheses contain standard errors clustered at date level. Significance: $*p < 0.1$, $**p < 0.05$, and $***p < 0.01$.

Table 11: DD Estimates using log AQI with Continuous Time Measurement

	Dependent variable: $\ln AQI$		
	(1)	(2)	(3)
(Days Post-Open) * 1(Dist.≤2km)	−0.002***	−0.002***	−0.003***
	(0.001)	(0.001)	(0.001)
Temperature ^0C	0.010***	0.010***	0.012***
	(0.003)	(0.003)	(0.003)
Relative humididy (%)	0.015***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)
Rainfall/snowmelt (mm)	−0.006*	−0.006*	−0.006
	(0.004)	(0.004)	(0.004)
Wind speed (m/s)	−0.104***	−0.106***	−0.103***
	(0.034)	(0.034)	(0.034)
Constant	3.836***	3.843***	3.761***
	(0.140)	(0.152)	(0.153)
Wind directions	Y	Y	Y
Wind speed * Wind dir.	Y	Y	Y
Year FE	Y	Y	Y
Season FE	Y	Y	Y
Day of Week FE	Y	Y	Y
Station FE	Y	Y	Y
Station FE*Tailno	N	Y	Y
Time trend	N	N	Y
Time trend * Station FE	N	N	Y
N	17230	17230	17230
R^2	0.53	0.53	0.54
F	47.84	22.79	24.66

Note: Each column reports results from an OLS regression where the dependent variable is log AQI and the key explanatory variable is the treatment indicator (the interaction of number of days after an opening and the treated group indicator). The treatment group is defined as the monitoring stations within 2km of a new subway line while the control group is defined as the monitoring stations more than 20km away from the new subway line. The unit of observation is station-day. The weather control 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 day-of-week, month-of-year, holiday-of-sample dummies. Spatial fixed effects include dummies for air pollution monitoring stations . Parentheses contain standard errors clustered at date level. Significance: $*p < 0.1$, $**p < 0.05$, and $***p < 0.01$.

Table 12: DD Estimates using log AQI with Heterogenous Effect

	Dependent variable:		
	(1)	(2)	(3)
# of New SWS (≤2km)	−0.021***	−0.026***	−0.031***
	(0.007)	(0.007)	(0.007)
Temperature ^0C	0.010***	0.010***	0.012***
	(0.003)	(0.003)	(0.003)
Relative humididy (%)	0.015***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)
Rainfall/snowmelt (mm)	−0.006*	−0.007*	−0.006
	(0.004)	(0.004)	(0.004)
Wind speed (m/s)	−0.105***	−0.106***	−0.103***
	(0.034)	(0.035)	(0.034)
Constant	3.814***	3.824***	3.736***
	(0.140)	(0.152)	(0.152)
Wind directions	Y	Y	Y
Wind speed * Wind dir.	Y	Y	Y
Year FE	Y	Y	Y
Season FE	Y	Y	Y
Day of Week FE	Y	Y	Y
Station FE	Y	Y	Y
Station FE*Tailno	N	Y	Y
Time trend	N	N	Y
Time trend * Station FE	N	N	Y
N	17230	17230	17230
R^2	0.53	0.53	0.54
F	47.92	22.77	24.75

Note: Each column reports results from an OLS regression where the dependent variable is log AQI and the key explanatory variable is the number of new subway stations within 2km of each monitor. The control group is defined as the monitoring stations more than 20km away from the new subway line. The unit of observation is station-day. The weather control 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 day-of-week, month-of-year, holiday-of-sample dummies. Spatial fixed effects include dummies for air pollution monitoring stations . Parentheses contain standard errors clustered at date level. Significance: *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

Table 13: Impact of Subway Expansion on Air Quality

Opening Date	Line	Length (km)	Total Density	△ in Density	% Reduction in AQI
Before 2008	1, 2, 5, 13, BT	140	26.55	-	-
19-Jul-08	8, 10, AE	57	37.59	11.03	6.62
28-Sep-09	4	28	43.89	6.3	3.78
30-Dec-10	15, DX, CP, FS, YZ	108	55.75	11.85	7.11
31-Dec-11	9	36	60.82	5.08	3.05
30-Dec-12	6	70	78.26	17.44	10.46
5-May-13	14 (West)	14	80.24	1.98	1.19
28-Dec-13	8 (Extension)	7	82.09	1.85	1.11
28-Dec-14	7	62	90.14	8.05	4.83
26-Dec-15	14 (East)	11	91.82	1.68	1.01
31-Dec-16	16	20	92.97	1.15	0.69

Notes: The names of suburban subway lines are shown as abbreviation.
AE: Airport Express; BT: Batong; DX: Daxing; CP: Changping; FS: Fangshan; YZ: Yizhuang
The % Reduction in AQI is based on the IV estimates in Table 7.

Table 14: Cost-Benefit Analysis of Subway Expansion (10-Year Discounted)

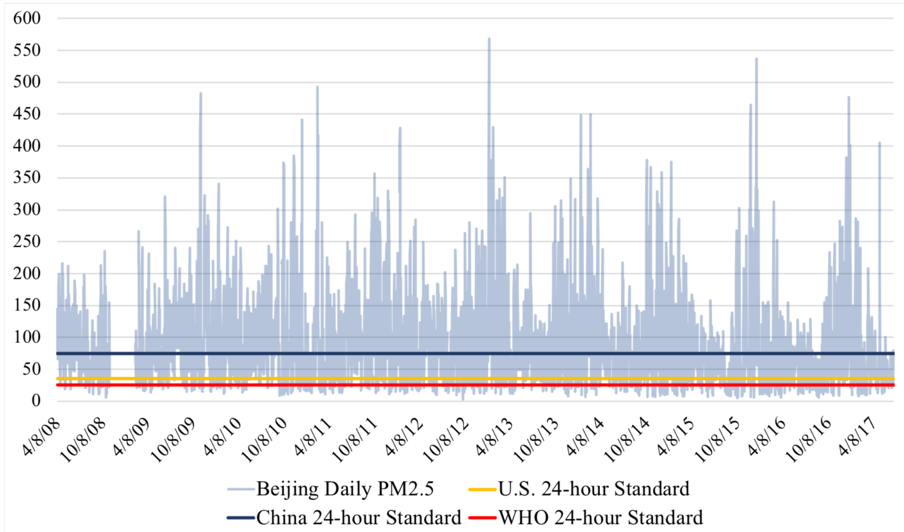
Opening Date	Total Cost (Billion $)	Total Discounted Health Benefit (10-year, Billion $)	Health Benefit/cost (%)	Total Discounted Congestion Benefit (10-year, Billion $)	Congestion Benefit/Cost (%)
19-Jul-08	5.68	3.55	62.4	2.69	47.2
28-Sep-09	3.61	2.13	58.9	2.69	74.3
30-Dec-10	7.04	4.22	59.9	2.69	38.1
31-Dec-11	5.18	1.77	34.1	2.69	51.7
30-Dec-12	10.3	5.86	56.5	2.69	25.8
5-May-13	3.15	0.91	28.8	2.69	85.2
28-Dec-13	1.95	0.85	43.5	2.69	137
28-Dec-14	11.5	3.86	33.3	2.69	23.1
26-Dec-15	2.94	0.75	25.6	2.69	91.2
31-Dec-16	4.8	0.48	10	2.69	55.8
Total	56.3	24.4	43.3	26.9	47.6

Notes: the monetary terms are all in 2015 dollars. The annual discount rate is assumed to be 5%. The total cost includes both the construction cost and the operating cost (10-year discounted total). The construction cost accounts for 82.9 % of the total cost during a 10-year period for the lines in the sample period.

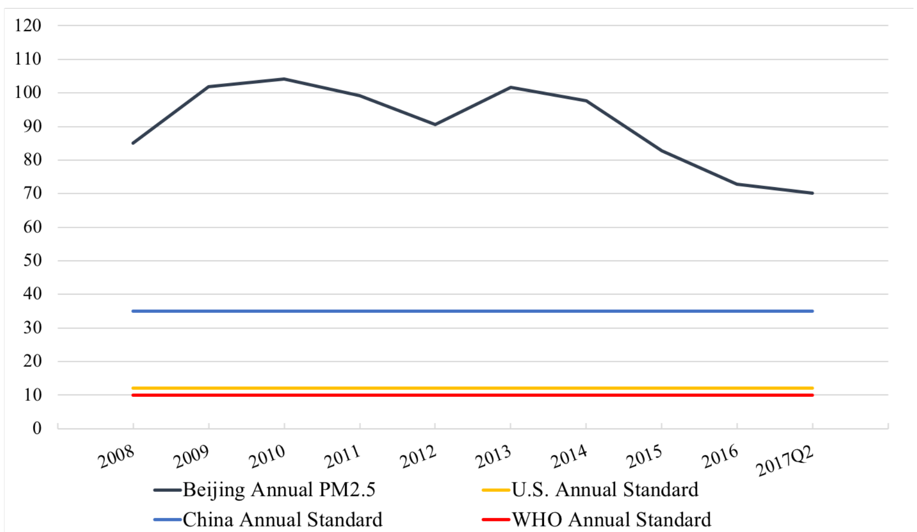
Table 15: Cost-Benefit Analysis of Subway Expansion (20-Year Discounted)

Opening Date	Total Cost (Billion \$)	Total Discounted Health Benefit (20-year, Billion \$)	Health Benefit/cost (%)	Total Discounted Congestion Benefit (20-year, Billion \$)	Congestion Benefit/Cost (%)
19-Jul-08	6.2	5.47	88.2	4.15	66.7
28-Sep-09	4.1	3.28	79.4	4.15	100
30-Dec-10	7.5	6.52	86.1	4.15	54.7
31-Dec-11	5.7	2.73	47.9	4.15	72.5
30-Dec-12	10	9.05	83	4.15	38
5-May-13	3.6	1.4	38.2	4.15	112
28-Dec-13	2.4	1.31	52.9	4.15	167
28-Dec-14	12	5.96	49.2	4.15	34.2
26-Dec-15	3.4	1.16	33.5	4.15	119
31-Dec-16	5.3	0.74	13.9	4.15	77.7
Total	71	37.6	52.8	41.5	58.2

Notes: the monetary terms are all in 2015 dollars. The annual discount rate is assumed to be 5%. The total cost includes both the construction cost and the operating cost (20-year discounted total). The construction cost accounts for 65.6 % of the total cost during a 20-year period for the lines in the sample period.



(a) Daily PM2.5



(b) Annually PM2.5

Figure 1: Beijing PM2.5 Density ($\mu g/m^3$) from US Embassy

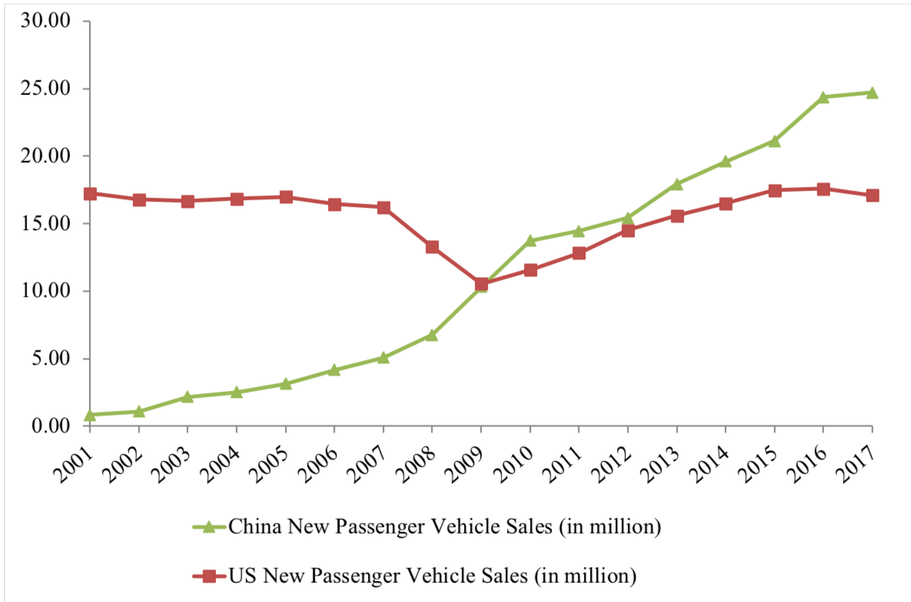


Figure 2: Vehicle Sales Development in China, Millions of Units, 2001-2017

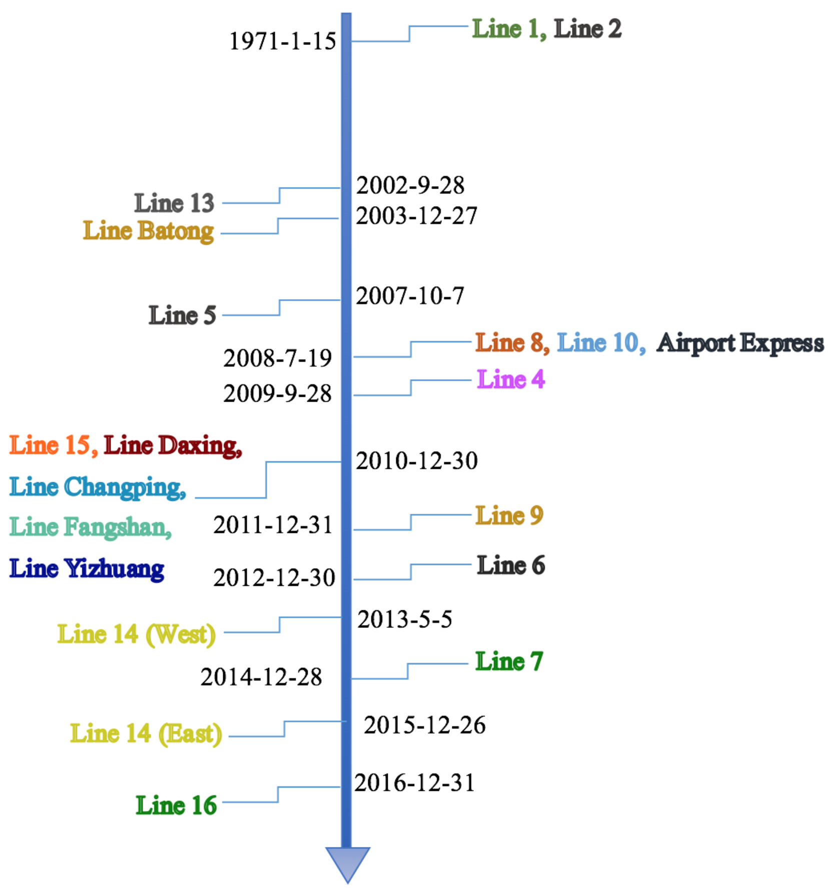


Figure 3: Beijing Subway Expansion Timeline

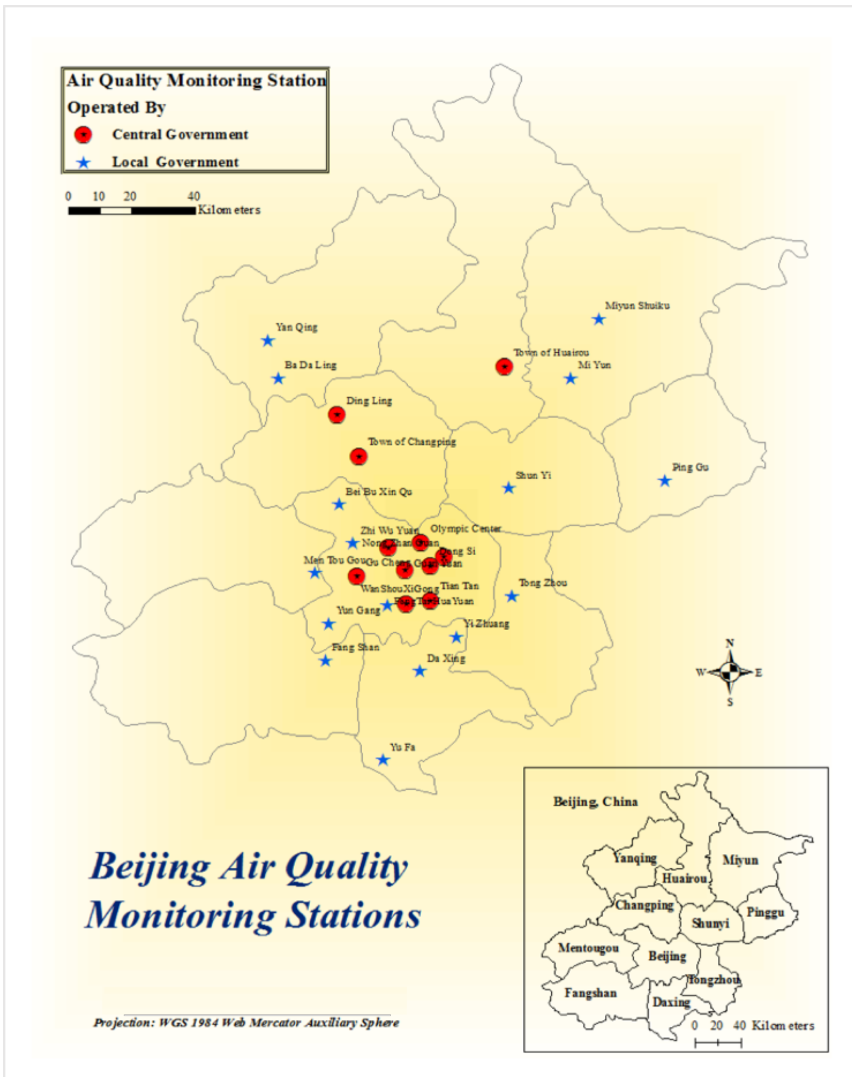


Figure 4: Beijing Air Quality Monitoring Stations

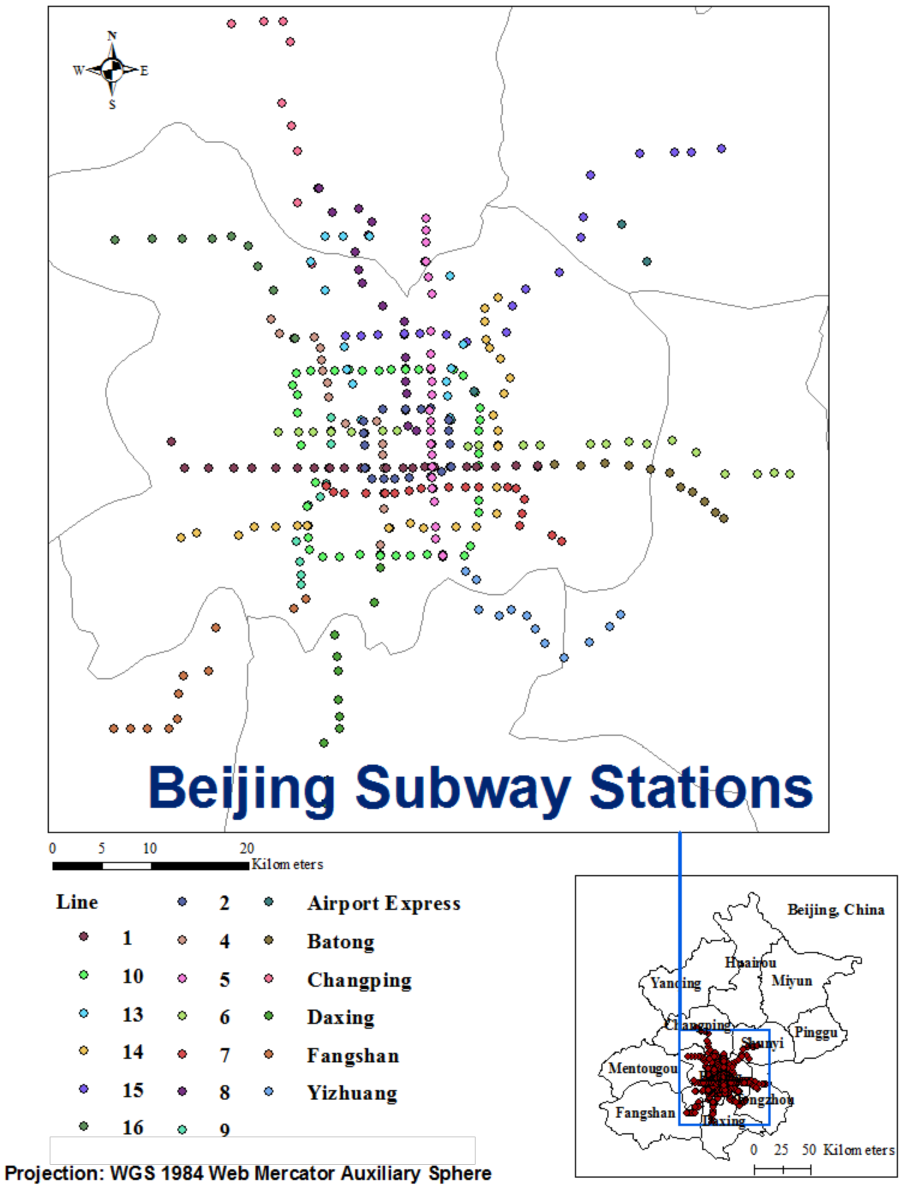


Figure 5: Beijing Subway Stations

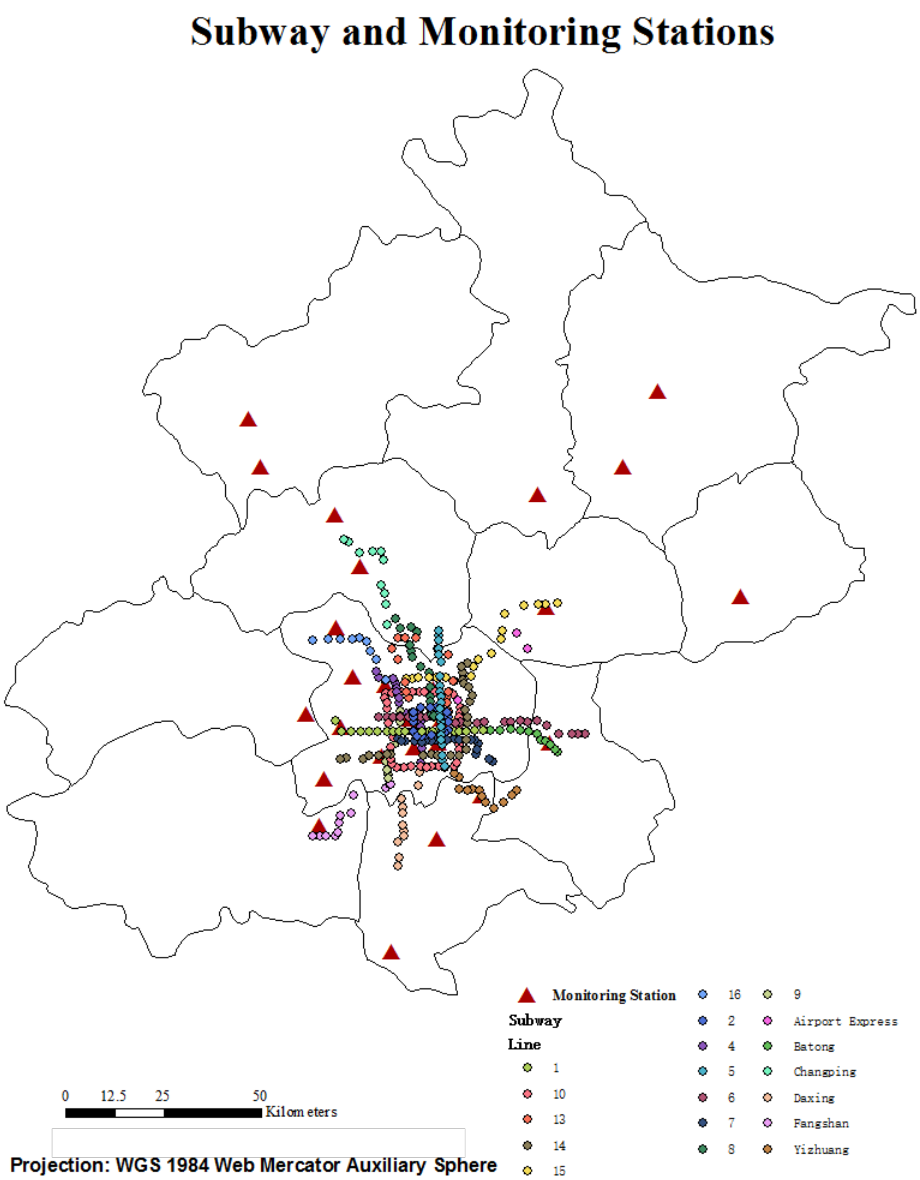


Figure 6: Beijing Monitoring Stations and Subway Stations

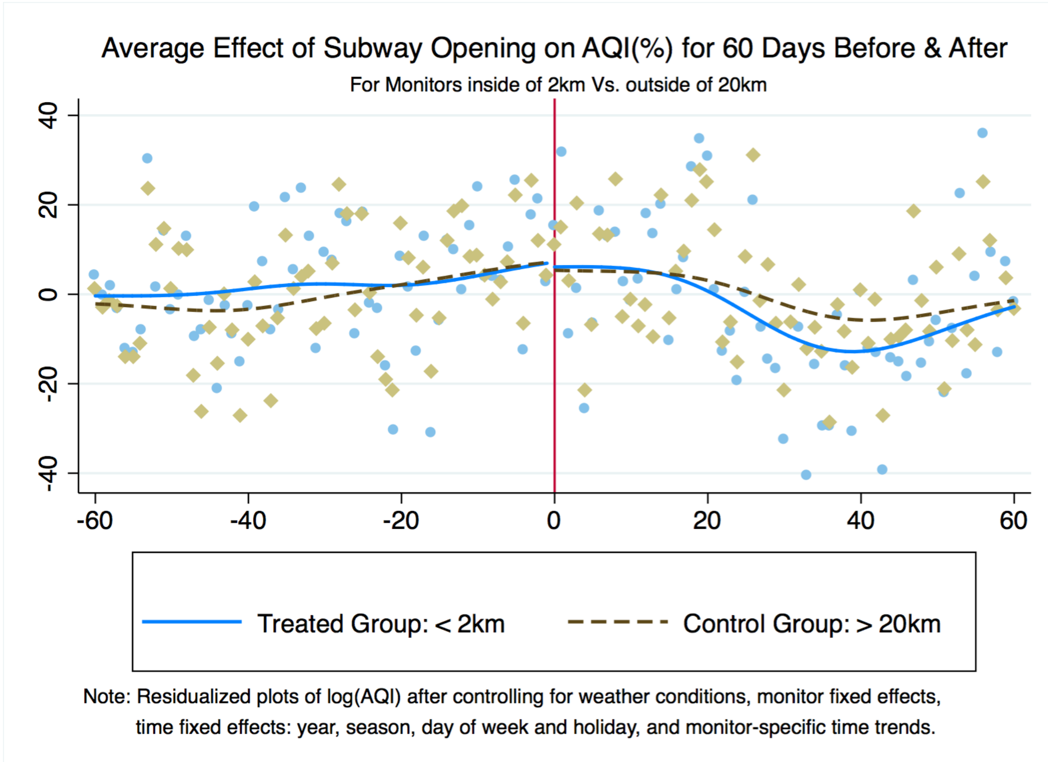


Figure 7: Average Effect of Subway Opening on AQI (%)

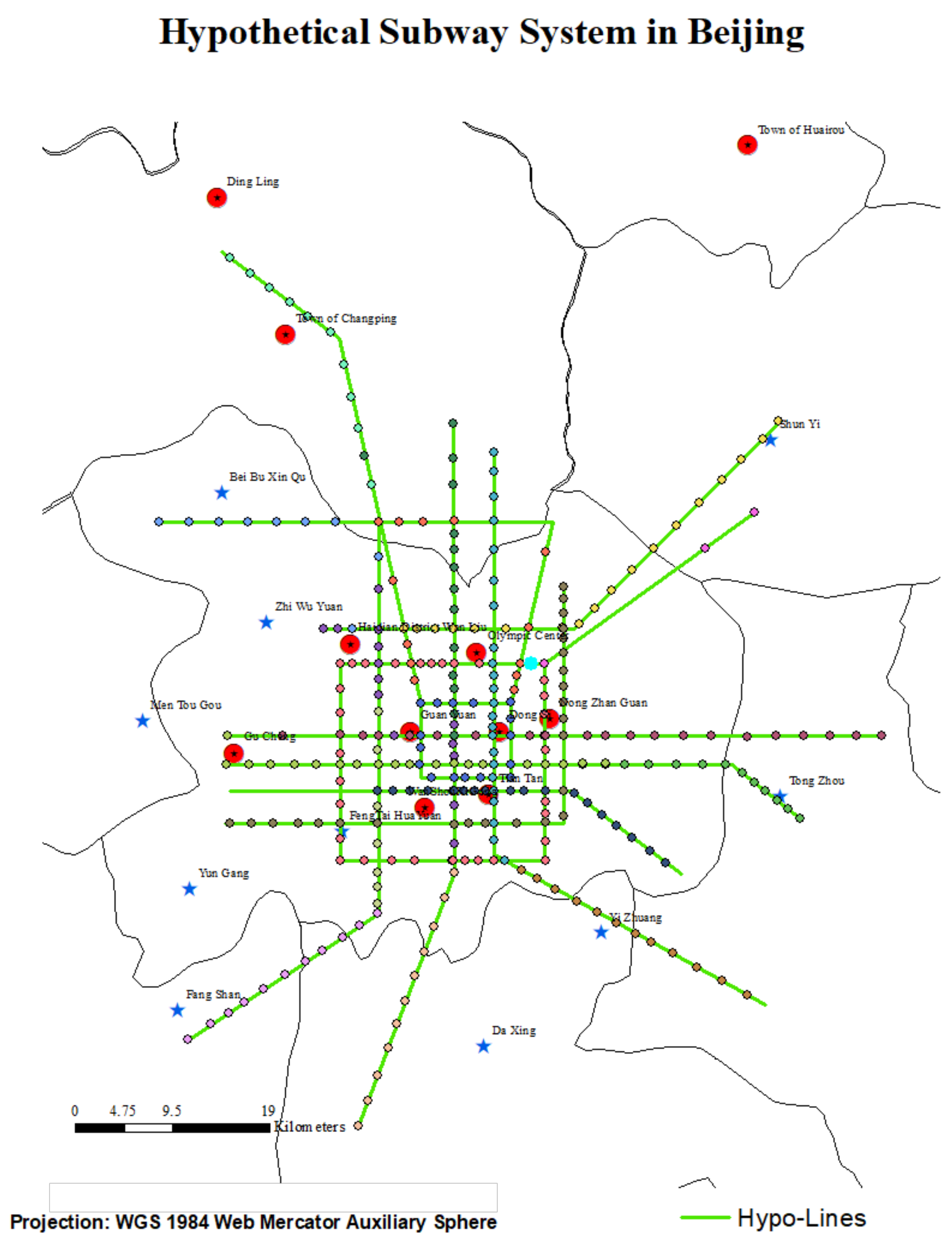


Figure 8: Hypothetical Subway System in Beijing