Building Subway Systems and Improving Air Quality in China: New Evidence from Multiple Chinese Cities

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Abstract

Automobiles are a major contributor to pervasive urban air quality problems worldwide. Partly to reduce these air quality problems, China has invested heavily in urban subway systems. This paper provides the first comprehensive estimates of the effects of these investments on urban air quality. The analysis uses a unique data set that combines hourly air quality data, daily meteorological data, and characteristics of cities for all major Chinese subway projects in 2013 and 2014. Exploiting the timing of subway openings, we find that the average opening reduced air pollution by 17%. We report substantial heterogeneity across time and cities: reductions are largest during daytime rush hours and in cities with low income and high population density. There is also evidence of diminishing marginal effects, as the air quality reduction declines with the number of existing stations. Back-of-the-envelope calculations suggest that air quality benefits of subway station opening are substantial compared to construction costs.

Keywords: Air quality, urban rail transit, traffic-related air pollution, discontinuity-based ordinary least squares model

JEL Classification: L92, Q53, R41, R53

Contents

1. Introduction

Extremely poor urban air quality has unfortunately accompanied rapid economic growth in many major cities in developing countries. The adverse human health effects of automobile tailpipe emissions include cardiopulmonary disease, respiratory infection, lung cancer, infant mortality, and childhood asthma (EPA 2004, Chay and Greenstone 2003, Currie and Neidell 2005, Neidell 2004). The World Health Organization (WHO) estimates that urban air pollution accounts for 6.4 million years of life lost worldwide annually (Cohen et al. 2004). Automobiles are a particularly important contributor to urban air quality problems, due to their emission of small particulates (PM2.5), carbon monoxide (CO), nitrogen oxides (NOx), and other pollutants. Moreover, traffic congestion exacerbates air pollution in urban areas (Gibson and Carnovale 2015; Chen et al. 2015).

To reduce air quality problems caused by automobiles, many countries have turned to policies that either raise the cost of owning and using automobiles or reduce the costs of alternative transportation modes.[1] For example, many cities restrict or tax the use of vehicles, either by taxing entry into the city center at certain times of day, or outright banning certain vehicles from entering the city center on certain days. In addition, many cities ration new license plates and limit the growth of automobile ownership. Whereas the driving restrictions have had mixed effects on air quality (e.g., Davis 20008, Cao et al. 2014, Sun et al. 2014, Viard and Fu 2015), ownership restrictions have been more effective (Yang et al. 2017). However, the costs of both types of vehicle policies have been high compared to the benefits (Blackman et al. 2018 and Li 2018).

Besides these vehicle policies, many cities have invested heavily in urban rail transit systems. Expanding public rail transit systems reduces the time cost of using this transit option, potentially reducing driving and the associated air pollution (Kain 1968, Vickrey 1969, Chen and Whalley 2012). Worldwide, about 155 million passengers per day in over 116 cities used urban rail transit in 2006, and those numbers are growing (Hester and Harrison 2009). Since the beginning of 2015, 57 cities opened or extended metro, tram, and light rail systems, with many of those openings occurring in developing countries.[2]

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[1] Reducing traffic congestion has also motivated many of these policies. Many studies have found small effects of public transit on congestion and vehicle miles traveled (e.g., Stopher 2003, Duranton and Turner 2011, Xie 2016). Whereas Anderson (2014) found that public transit in Los Angeles reduces congestion, Yang et al. (2015) found that Beijing's subway system has had little effect on the city's traffic congestion.

[2] Data source: http://www.urbanrail.net/news.htm#nowopen

China is a prominent example of these problems and policy responses. Major Chinese cities suffer from some of the worst air pollution in the world. China's Ministry of Environmental Protection announced that in 2013 only 3 of 74 large Chinese cities met official air quality standards. In Beijing, where vehicle ownership has increased five-fold, the concentration of PM2.5 was eight times greater than the 2013 WHO guidelines, and vehicle emissions account for about 20 percent of Beijing's PM2.5 emissions (BMEPU, 2014).

To cope with these urban air pollution problems caused by vehicle use, China has restricted automobile use and rationed new license plates to limit growth in vehicle ownership. In addition, China has invested heavily in public transportation. A total of 96 lines in 35 Chinese cities were built or extended between 2013 and 2018. China's urban rail transit system is projected to have 6000 kilometers of track by 2020.[3] By investing $30 billion, between 2002 and 2014 Beijing increased the size of its subway system by almost a factor of 10, and the number of stations increased from 39 to more than 300 (Xie, 2016).

Despite China's massive investments in public transportation and continuing concerns about pervasive air quality problems, there is little evidence on whether these investments have improved air quality. Chen and Whalley (2012) found that the opening of Taipei's subway system reduced carbon monoxide by 5 to 15 percent but had little effect on ground level ozone. Gendron-Carrier et al. (2015) examined the effect of subway openings on air quality across the world, including 11 openings in China. They found that particulate concentrations dropped by 4% on average following a subway system opening and that the effect was larger near the city center. Their data do not include the dozens of openings in China since 2013, when China's subway systems have grown rapidly. Other cost-benefit analyses of Chinese urban rail transit systems documented the substitution of travel modes, but they did not quantity air quality improvements (e.g. Miao 1996, Fan 2012, Lu 2012, Xie 2016).

In this paper, we study the 15 Chinese subway line openings in 2013 and 2014. We employ a discontinuity-based ordinary least squares (DB-OLS) analysis of hourly measurements of air pollution around the time of the openings. Specifically, we test for a discontinuity in air pollution levels after the stations open, controlling for meteorological factors that may affect pollution and including polynomial time trends to control for other factors. We find that opening subway stations alleviates air pollution, especially during rush hours in the daytime. These findings are intuitive, given that ridership typically peaks during daytime rush hours. The effects are smaller in the cities with higher

[3] Data source: http://mic-ro.com/metro/metrostats.html

income and more subway lines, and are larger in the cities with higher population density. Furthermore, the effect of the first subway line opening is stronger, compared to expansion of an existing subway system. We find no evidence of structural breaks in other variables that affect pollution, including meteorological variables.

According to back-of-the-envelope calculations, on average each station opening yields benefits of roughly $3 billion, which is considerably larger than the average costs of building a station. Although these are rough calculations, they suggest that environmental benefits are an important consideration in benefit-cost analysis of public investments in subway infrastructure.

Methodologically, our paper is similar to Chen and Whalley (2012) and Gendron-Carrier et al. (2018), who also use DB-OLS. There are several differences between our analysis and theirs. First, we include a large set of recent openings in China. This contrasts with the single opening in Taipei that Chen and Whalley (2012) analyzed. Gendron-Carrier et al. (2018) included a large set of openings from around the world, 11 of which are in China, but their openings in China occurred prior to ours. Our period includes rapid growth in incomes and vehicle use, which could cause the effects of the subway openings to differ from those estimated in prior analyses. Second, whereas Gendron-Carrier et al. (2018) used monthly data, we use hourly data, which allows us to control for potentially nonlinear relationships among air pollution and other factors that change frequently, such as weather. Moreover, we use the hourly data to compare the effects across periods of a day, motivated by two facts: daytime pollution is more harmful than nighttime pollution because more people are outside during the daytime, and subway ridership is typically highest during the daytime. Third, we examine a broader set of air pollutants. We consider five air pollutants that are associated with vehicle use (carbon monoxide, PM2.5, PM10, nitrogen oxides, and sulfur dioxide)[4], as well as one summary measure of air quality (AQI), whereas Chen and Whalley (2013) examined carbon monoxide and nitrogen oxides, and Gendron-Carrier et al. (2018) used a proxy for air pollution based on satellite observations.

The reminder of the paper proceeds as follows. Section 2 introduces the data set, combined from different data sources. Section 3 presents the methodology, and Sections 4 through 6 present the regression results, report a set of robustness checks, and discuss heterogeneous effects. Section 7 concludes.

[4] Although Chen and Whalley (2012) considered sulfur dioxide a pollutant that is not caused by traffic, the case in mainland China is different. During 2013 and 2014, the period studied in this paper, the gasoline in China followed the third and the fourth standards (GB 17930-2011), which require the sulfur content to be under 150mg/kg or 50mg/kg respectively. This indicates that vehicle exhaust pipes can be a source of sulfur dioxide. Data resource: http://www.gb688.cn/bzgk/gb/newGbInfo?hcno=6B19D7AEEB1895A99C00518B67629600

2. Data

We combine four major data sets that include the dates of subway station openings in China between 2013 and 2014; hourly air pollution data from monitors distributed across China; daily weather data by meteorological stations; and data on city characteristics. The data sources and the details of the variables are discussed below.

Dates of subway openings. The sample includes cities that opened a new subway system or that added lines to existing systems in 2013 and 2014. We collect most of the opening dates from the official website of subway operating companies. If the website does not provide the exact date, we determine the date from a news search.

Information on subway openings is summarized in Figure 1 and Table 1. Figure 1 depicts the cities with subway line openings in 2013 and 2014, the number of newly added subway stations, and the existing stations. Table 1 lists the station openings, which include 15 subway lines in 11 cities. In total, 237 stations were added.

One concern about the empirical strategy is that the opening of a station may be correlated with unobserved determinants of air pollution. For example, if openings typically occur on a particular weekday or weekend day, and the vehicle use pattern on that day is different from other days, estimates would be biased. According to Table 1, most of the openings occurred at the beginning or the end of a month, rather than on a fixed weekday or weekend day. This alleviates concerns about omitted variables correlated with the day of the week. However, Dalian, Changsha and the second line of Kunming opened around May 1, which is Labor Day and is typically followed by a multi-day holiday. Industrial activities and vehicle use are the major emission sources, and these emissions are very different on holidays than on other days. Because it would be difficult to disentangle the effects of these two openings from the effects of the holidays, we drop these lines from the empirical analysis.

Air pollution data. We collect hourly air quality data from the website of the Ministry of Environmental Protection (MEP). They start on January 1, 2013 and cover all of the hundreds of air quality monitors in large cities in China. The concentrations of PM2.5 (fine particulates), PM10 (larger particulates), nitrogen oxides, carbon monoxide, sulfur dioxide, and ozone are recorded by the monitors and

reported by a real-time reporting system of MEP.[5] All of these pollutants harm human health and the environment, and vehicles are major causes of all of them.

The Air Quality Index (AQI) is calculated based on the concentration of these recorded pollutants.[6] The range of AQI in China is from 0 to 500, and a higher AQI indicates worse air quality. The air quality is classified as "Excellent" when AQI is less than 50, "Good" between 50 and 100, "Slightly Polluted" between 101 and 150, "Moderately Polluted" between 151 and 200, "Heavily Polluted" between 201 and 300, and "Severely Polluted" over 300.[7] In 2013, the average AQI of the cities studied in this paper was about 110.

Table 2 presents summary statistics of the air pollution variables and other variables included in the empirical analysis. Panel A shows mean pollution levels during the two weeks prior to and following the subway expansions. Column 3 shows substantial and statistically significant decreases in means after the expansions for all pollutants except for nitrogen oxides. For example, the AQI declined by about 16 percent.

Weather data. Meteorological conditions can affect pollution levels. For example, particulate matter, the main pollutant in China, can be washed or blown away by precipitation and wind. To control for the effects of weather on air quality, we collect daily meteorological data. Panel B shows summary statistics for the meteorological variables. The differences in means, shown in column 3, are large and statistically significant for some of the variables, indicating the importance of controlling for the meteorological variables that may affect pollution.

City characteristics. To investigate the heterogeneity in the effects of subway opening on air pollution, we collect information from yearbooks on city characteristics, such as per capita income. Columns 6 through 10 of Table 1 report the city characteristics.

[5] Zhang and Mu (2017) find that the quality of air pollution data has improved significantly since 2010, and that the real-time reporting system of MEP contributes to the improvement.

[6] The calculation varies across countries. For example, when the concentration of PM2.5 is 35 µg/m3, China computes the index as 50, whereas the US calculates the index as 100. For more information on the calculation differences, refer to https://www.cnblogs.com/tiandi/p/6158576.html

[7] Technical Regulation on Ambient Air Quality Index (GB3095-2012).

3. Estimation Strategy

Following the literature, we employ a DB-OLS methodology. Chen and Whalley (2012) use daily measurements of air pollution and regress air pollution on a polynomial in time and a discrete jump in the polynomial at the time of the opening. The polynomial controls for unobserved factors that affect pollution and that do not jump discretely at the time of the opening.

We make several improvements on their methodology, utilizing the three attributes of our data: a) the data cover multiple cities; b) the pollution data are measured at the hourly time step; and c) we directly control for meteorological conditions. We identify the effect of subway opening on air quality by estimating the following equation:

$$y_{it} = \beta_0 + \beta open_{it} + \boldsymbol{P(t)}'\boldsymbol{\delta} + \boldsymbol{P(t)}'\boldsymbol{\gamma} \times open_{it} + \boldsymbol{X}_{\boldsymbol{it}}'\boldsymbol{\theta} + \boldsymbol{\gamma_{it}} + \alpha_i + \epsilon_{it},$$

$$where - h < t < h. \qquad (1)$$

The dependent variable, y_{it}, is the log of air quality in city i at time t; $open_{it}$ is a dummy variable which equals one for all hours after the subway opening in city i, and zero for the observations before the opening; the vector $\boldsymbol{P(t)}$ is a polynomial in time; the vector $\boldsymbol{X_{it}}$ is a set of interactions of daily meteorological variables (wind, precipitation, pressure and temperature) and hour dummies; the vector $\boldsymbol{\gamma_{it}}$ is a set of dummy variables, including whether the day is a holiday, whether the day is during a weekend, and whether central heating (district-wide seasonal heating) is provided in city j at time t. The polynomial controls for time trends in pollution in the absence of the opening. The meteorological variables affect pollution levels conditional on emissions. For example, winds may blow pollution from factories located in a different city that is upwind from the city in which we are collecting data. α_i is a city fixed effect, controlling for the effect of time-invariant city characteristics on air quality; ϵ_{it} is the error term; and h is the bandwidth, which determines which observations are included in the estimation of equation (1).

We estimate equation (1) separately for the AQI and each of the six air pollutants from Table 2. According to previous literature, automobile exhaust mainly contributes to carbon monoxide, PM2.5, PM10, nitrogen oxides, and sulfur dioxide concentration levels. We therefore expect negative effects on these five pollutants as well as AQI. The effect on ozone is more complicated, because ozone forms when nitrogen oxides combine with volatile organic compounds in the presence of sunlight, which is a highly nonlinear process (Seinfeld and Pandis 1998). Moreover, in certain situations a decrease in nitrogen oxides emissions could raise ozone levels (Li et al. 2019). Because the subway

openings should reduce vehicle use and emissions, we expect the openings to reduce AQI and levels of each of the five pollutants other than nitrogen oxides; the effect on nitrogen oxides could be positive or negative.

The parameter β captures the average effect on air quality of the subway openings studied in this paper. In Section 6, we allow the effect to vary across cities. As with any DB-OLS, the estimate of β is unbiased if there are no variables (included in the estimation or omitted) that affect air quality and jump discretely during the bandwidth after the opening. Because equation (1) includes a polynomial time trend, the estimate is unbiased if variables that affect air quality change smoothly within the bandwidth of the opening date (Hahn et al., 2001). In our case, weather could affect air quality and in fact Table 2 shows differences in means of weather variables before and after the subway openings. However, these differences appear not to create bias, because Figure 2 shows that none of the meteorological variables jump discontinuously at the time of the opening. Thus, the difference in means in Table 2 appears to reflect smooth trends over time.

As Imbens and Kalyanaraman (2009) suggest, the choice of bandwidth is critical to estimation. A smaller bandwidth may reduce bias and increase variance of the estimate, whereas a larger bandwidth increases bias and reduces variance. Because travel behavior exhibits a weekly periodicity, we use 2 weeks (14 days) as the bandwidth in the main regression (i.e., the sample includes 28 days centered on the opening). We consider alternative bandwidths as robustness checks.[8]

[8] We calculate the optimal bandwidth using the method suggested by Imbens and Kalyanaraman (2009), and the result is around 3-4 hours. However, a subway opening likely affects air quality over a longer time, and using such a short bandwidth would underestimate the effects of the openings. As noted by Hausman and Rapson (2018), this is a common problem in the framework of Regression Discontinuity in Time (RDiT), because it often has insufficient cross-sectional identifying variation. Alternatively, Chen and Whalley (2012) use 15 days as the bandwidth (30-day window) to identify the effect.

4. Main Results

Before reporting estimates of equation (1), we provide a graphical analysis of the changes in air pollution after the subway openings. Figure 3 plots the level of pollutants on the vertical axis against the time relative to the opening event. We fit the kernel regressions to the pollutants separately for the day before and after the opening (the red vertical line indicates the opening). Figure 3 shows a noticeable drop in pollution levels at the time of the openings.

To quantify the air pollution changes depicted in Figure 3, we estimate equation (1) separately for each of the air pollutant variables and summarize the results in Table 3. Panel A reports a set of parsimonious regressions that include only the opening dummy and linear time trends before and after the opening. Panel B also includes the meteorological variables, dummies for weekend, holiday, and heating seasons for northern cities, and city fixed effects. As shown by the two panels, the results are stable across specifications for most of the pollutants.

We take the specification with controls (Panel B) as the main results. Across the cities in the sample, the average opening decreased AQI by 17%, PM2.5 by 19%, PM10 by 19%, nitrogen oxides by 12%, carbon monoxide by 5%, and sulfur dioxide by 19%. All estimates are significant at the one percent level, except for carbon monoxide, which is significant at the 5 percent level.[9] The openings increase ozone levels by about 12%. The possible reason is the negative relationship between PM2.5, nitrogen oxides and ozone (Li et al. 2019). The opening deceases PM2.5 and nitrogen oxides, and therefore increases ozone. Comparison between Panel A and Panel B shows that decreases in all pollutants except ozone are insensitive to adding the meteorological controls and fixed effects. This robustness supports the exogeneity of the subway openings to trend breaks in other determinants of pollution levels.

To visualize the regression results for each dependent variable, Figure 4 plots residuals after partialling out the meteorological variables and fixed effects. The figure also shows the fitted time trends before and after the openings. Except for ozone, the figure indicates sharp drops in the concentration levels on the day of the subway opening.

In Figure 4 and Table 3, the trends are typically positive prior to the opening and negative afterwards. There are two main explanations for this change in the direction of the trend. First, a factor other than the opening could have caused the change. For example, pollution levels may exhibit mean reversion,

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[9] Robust standard errors are used. The results remain significant at the 5% level when standard errors are clustered at nine hours or below

in which case a positive trend would be followed by a negative trend. As discussed above, this situation would not bias the estimate of the opening variable, as long as another factor did not simultaneously cause a jump in the trend at the time of the opening.

A second possible explanation is that the openings caused the trend to shift from being positive to negative. In that case, the opening dummy would underestimate the effects of the opening on pollution levels. For that reason, we consider the opening dummy coefficient to be a conservative estimate of the effects of the openings on pollution.

So far, we document strong evidence that subway station openings reduce air pollution. This leads to huge economic benefit. Because PM2.5 is more harmful than PM10 and most major urban areas in China have high levels of PM2.5, we focus on PM2.5 when estimating the economic benefits. We use the methodology that follows the Energy Policy Institute at the University of Chicago[10] to estimate the benefits of reducing PM2.5 levels. Their report on Air Quality Life Index (AQLI) found that a 10 $\mu g/m^3$ increase in PM2.5 reduces life expectancy by 0.98 years. According to the main regression, the average subway opening reduced PM2.5 by 18.6% from the sample mean of 93 $\mu g/m^3$. By a back-of-envelop calculation, we find that a typical subway opening increased the life expectancy of nearby residents by 1.7 years.

Next, we translate the life expectancy effect into dollars using annual per capita income as a proxy for the value of a life year. In our sample of cities with subway openings, the average annual income is 35 thousand yuan (5.7 thousand U.S. dollars according to the 2013 exchange rate). Multiplying the change in life expectancy (1.7 years) by the annual income (5.7 thousand dollars) and the average urban population in a city (5.64 million) yields the average benefit of a new subway line, which is 54.86 billion dollars. Given that the average number of stations of a new subway line is 15.8, we find that the health benefit per station is 3.5 billion dollars. For comparison, the average cost of constructing a new subway station is about 0.17 billion dollars[11]. While the calculation is rough, the result suggests that the environmental benefits of subway openings may be quite large, especially considering the fact that the calculations do not include the benefits of reducing other pollutants.

[10] https://aqli.epic.uchicago.edu/about/methodology

[11] According to the official document (document number: 000013039-2013-00176) released in 2013, the investment in a subway line in Wuhan is 2.0 billion dollars, and there are 12 stations. http://zfxxgk.ndrc.gov.cn/web/iteminfo.jsp?id=12397

5. Robustness Checks

We perform several robustness checks in this section, including varying the bandwidth, varying the time trends, testing the exogeneity of the openings, and including lagged pollution and interactions.

In Section 3, we noted that the bandwidth choice inherently trades off bias and precision. Panel A of Table 4 shows the results using a one-month bandwidth and Panel B shows the results using a two-month bandwidth. The regressions are otherwise identical to those in Panel B of Table 3. The results are remarkably similar across alternative bandwidths. The longer bandwidth also addresses a potential concern about the stability of the effects over time. A new subway line could be an important event that attracts public attention. Therefore, on the opening day and in the week or two following the opening, there could be a large increase in ridership as people try out the new subway line. Ridership could increase or decrease over time, in which case the effects of opening on pollution would change over time. The similarity of the results across the one-week, two-week, and one-month bandwidths suggests that the effects are stable, at least out to a month after the opening. This result is not surprising because the openings do not represent new systems but rather additional stops in existing systems.

In principle, the estimated coefficient on the open dummy could be biased if pollution follows a nonlinear trend before or after the opening. To address this possibility, Panel A of Table 5 includes a quadratic polynomial and Panel B includes a kernel estimate of the time trend. As shown in Table 5, the results remain similar to the main results.

The exogeneity of the openings is a critical assumption in our specification. However, when the running variable is time, it is impossible to directly test the plausibility of the exogeneity assumption (Hausman and Rapson, 2018). As we mention in the previous section, the opening date is uncorrelated with the day of the week, which supports the exogeneity of opening to travel demand variation over the course of the week. Further supporting the exogeneity of the openings is the fact that we do not find evidence of structural breaks in other variables that affect pollution levels, including meteorological levels (see Figure 2). In addition to this evidence supporting our identification strategy, we use the "donut" RD method suggested by Barreca et al. (2011). We remove the day before and after the opening and run the identical regressions to those in Panel B of Table 3. This "donut" RD method alleviates concerns that the local government may have selected a particular opening date. The regression results are summarized in Table 6, and they are similar to the main results.

Considering that pollution may last for hours (Henderson, 1992). we control for the lagged air pollution levels. The results are listed in Panel A of Table 7. The sign of subway opening is still negative, with the coefficients becoming smaller. The reason is that, as Chen (2012) noted, the coefficient of $open$ measures a short time effect when the lagged dependent variable is included as a regressor. We therefore calculate the total effect for the regressions that have the lag term, following the method in Henderson (1996). We find that the magnitude is about half of that in the main regression. As for ozone, there is no significant change.

In addition, Equation (1) assumes by default that the covariates have the same effects on pollution levels across all cities. To relax this assumption, we add the interaction terms of city dummies with all other covariates in Equation (1), to allow for the effects of weather and the effects on weekend and holidays varying across cities. Table 8 shows that the coefficients of the open dummy are insensitive to adding these interaction terms.

6. Heterogeneous Effects

In this section, we investigate possible heterogeneity in the effects of subway opening across time of day and cities.

6.1. Heterogeneity across time of day

The effects of subway openings depend on the number of people who switch from driving to subway. We expect more people to switch during peak hours than during non-peak periods for two reasons. First, traffic congestion is particularly high during peak hours, which makes subways relatively more attractive during peak hours than during non-peak hours. Second, because more total people travel during peak hours than during non-peak hours, even if the proportion of people who switch does not vary across hours, we would expect more people to switch during rush hours.

To test whether the effects of subway openings vary across periods of the day, we define three time periods: night （1am to 3am), peak hours (6am to 8am), and non-peak daytime hours (10am to 12am). We estimate separate regressions for hours that belong to each of the three time periods. The regressions are otherwise the same as in Panel B of Table 3.

Results are reported in Table 9. It shows that, as expected, subway openings have the largest effects on peak hour pollution levels. Air quality at night is not affected, which is consistent with expectations because subway ridership is much lower during the night than during the day.

6.2. Heterogeneity in Income and Population Density

Consumers' responses to subway openings may depend on income. For example, consumers with high income may have stronger preferences for traveling by car. We examine this possibility by adding to the main specification of Equation (1) the interaction of the opening dummy with the city's average household income and the main term. We summarize the results in Panel A of Table 10. As expected, the income interaction is positive, meaning that cities with high income experience smaller (less negative) pollution changes.[12] We consider these results to be suggestive because income may

[12] Depending on the range of the income variable, some cities may have predicted increases in the pollutants. The threshold of income at which the total impact of subway openings equals zero is 43.8 thousand yuan. In our sample Ningbo and Shanghai's incomes are above the threshold by a small magnitude, indicating the increasing effect is close to zero.

be correlated with other variables that affect substitution between cars and subways, including the quality of other transportation options such as buses.

In addition, cities with greater population density are more likely to have traffic congestion. Consumers in those cities, therefore, may be more likely to switch from driving to subway when a subway line opens. As expected, Panel B of Table 10 shows that cities with high population density experience larger pollution decreases. Again, we treat these results as suggestive because population density may be correlated with other city attributes that affect substitution between subways and driving.

6.3. Heterogeneity in pre-existing subway stations

The first subway line in a city may attract more passengers than extending a line of an existing system. For example, an extension may incorporate areas with low population density, which could have a smaller effect on vehicle use compared to the system's first line, which is typically located in dense areas. In addition, the first subway line is likely to have a larger news effect than extension of a subway system, because people find more interest in new things. For these reasons, opening the first line could have a larger effect on pollution compared to subsequent openings. The results in Panels C and D of Table 10 are consistent with these expectations. New lines have larger effects on pollution than do other lines, and the pollution reduction diminishes with the number of stations that are in existence at the time of the opening.

Thus, the heterogeneity analysis suggests that the effects of subway openings vary considerably across time periods and cities. Although data limitations prevent us from identifying the underlying causes of this heterogeneity, policy makers considering a new opening should be aware that the effects may differ from the effects of previous openings.

7. Conclusion

Exposure to air pollution has substantial negative effects on health, and auto use contributes substantially to air pollution in urban areas. In this paper, we investigate whether urban rail transit expansion improves air quality. By exploiting the dates of the subway station openings using a DB-OLS approach, we find that opening subways significantly reduced traffic-related air pollution, which indicates that investment in public transportation infrastructure improved air quality.

We find that subway openings reduced air pollution more during the daytime than at night, and reduced pollution more during peak travel hours. We also find that the magnitudes of the changes are negatively correlated with income and positively correlated with population density. The more existing subway stations, the weaker the effect of opening a new subway line, and the first subway line has the strongest effect on air pollution. The heterogeneous effects can provide more information to policy makers on where to locate new subway lines in order to achieve the most pollution reduction.

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Tables and Figures

Table 1. New Subway Lines Opened in 2013 and 2014 in China

City (1)	Name of the Line (2)	Opening date (3)	Existing stations (4)	New stations (5)	Average household income (thousand yuan) (6)	Population density (people/km^2) (7)	Population in urban area (thousand persons) (8)	Gross regional product (billion yuan) (9)	General public budget revenue (billion yuan) (10)
Kunming	1	5/20/2013	3	12	28	594	2746	269	17
Xi'an	1	9/15/2013	17	19	33	1,621	5806	410	48
Guangzhou	6	12/28/2013	129	21	42	1,786	6866	1415	105
Wuhan	4	12/28/2013	47	15	30	1,885	5126	727	160
Zhengzhou	1	12/28/2013	0	20	27	5,119	5171	334	55
Shanghai	12	12/29/2013	338	15	44	3,809	13641	2134	407
Shanghai	16	12/29/2013	338	11	44	3,809	13641	2134	407
Changsha	2	4/29/2014	0	19	37	1,589	3035	492	48
Kunming	2	4/30/2014	15	14	31	599	2768	283	16
Dalian	12	5/1/2014	12	8	34	1,185	3043	354	62
Ningbo	1	5/30/2014	0	20	44	932	2296	459	60

Wuxi	1	7/1/2014	0	24	42	1,494	2457	422	47
Nanjing	10	7/1/2014	53	14	43	984	6487	882	90
Nanjing	S1	7/1/2014	53	8	43	984	6487	882	90
Nanjing	S8	8/1/2014	75	17	43	984	6487	882	90

Notes: The table lists the cities that opened subway stations during 2013 and 2014 in China. Columns 1 through 5 report the city, the name of the new subway line, the opening date, the number of subway stations that existed prior to the opening, and the number of new stations of this opening. Columns 6 through 10 report each city's economic characteristics during the year of the subway opening.

Table 2. Summary Statistics

Panel A: Pollutants

	Pre-opening (2874 city hours)		Post-opening (2995 city hours)		Difference
	(1)		(2)		(3)
Variable	Mean	Std. Dev.	Mean	Std. Dev.	
Air quality index (AQI)	124.68	1.66	104.60	1.14	-20.08 ***
PM2.5 ($\mu g/m^3$)	93.17	1.46	74.38	0.97	-18.79 ***
PM10 ($\mu g/m^3$)	131.90	1.83	111.20	1.24	-20.70 ***
Nitrogen oxides ($\mu g/m^3$)	53.62	0.59	52.91	0.59	-0.71
Carbon monoxide (mg/m3)	1.39	0.02	1.34	0.01	-0.05 **
Sulfur dioxide ($\mu g/m^3$)	41.49	0.96	35.16	0.68	-6.33 ***
Ozone ($\mu g/m^3$)	55.66	0.87	65.92	1.08	10.26 ***

Panel B: Weather

	Pre-opening (2874 city hours)		Post-opening (2995 city hours)		Difference
Variable	Mean	Std. Dev.	Mean	Variable	Mean
Wind speed (0.1m/s)	21.61	0.18	21.18	0.14	-0.42 *
Precipitation (0.1mm)	33.26	1.87	43.86	2.28	10.60 ***
Pressure (0.1hPa)	9845.76	11.84	9817.65	11.41	-28.116 *
Temperature (0.1℃)	147.60	1.78	162.17	1.62	14.57***

Notes: In Panels A and B, the data include observations two weeks before and after the subway openings. Columns 1 and 2 report mean and standard deviations of air pollution and weather before subway openings. Columns 3 and 4 report those after subway openings. The last column reports the difference and the p-value of a t-test for the difference between the post and pre-opening means. ***, **, and * indicate that the difference is statistically significant at the 1%, 5%, or 10% significance level, respectively.

Table 3. Effects of Subway Opening on Air Pollution

Panel A: Without control variables

	Air quality index	PM2.5	PM10	Nitrogen oxides	Carbon monoxide	Sulfur dioxide	Ozone
Open	-0.248***	-0.308***	-0.262***	-0.073**	-0.023	-0.232***	-0.012
	(0.030)	(0.038)	(0.032)	(0.032)	(0.024)	(0.044)	(0.050)
Trend before opening	0.083***	0.090***	0.097***	0.059***	0.026**	0.153***	0.001
	(0.012)	(0.015)	(0.013)	(0.011)	(0.011)	(0.017)	(0.018)
Trend after opening	-0.087***	-0.086***	-0.103***	-0.091***	-0.017	-0.217***	0.060**
	(0.015)	(0.020)	(0.017)	(0.015)	(0.013)	(0.023)	(0.026)
Bandwidth	14days	14 days	14 days	14 days	14 days	14 days	14 days
R-squared	0.017	0.016	0.016	0.007	0.002	0.021	0.005
Observations	5,869	5,869	5,869	5,869	5,869	5,869	5,869

Panel B: With control variables

	Air quality index	PM2.5	PM10	Nitrogen oxides	Carbon monoxide	Sulfur dioxide	Ozone
Open	-0.166***	-0.186***	-0.193***	-0.119***	-0.049**	-0.185***	0.123***
	(0.027)	(0.033)	(0.031)	(0.023)	(0.020)	(0.031)	(0.037)
Trend before opening	0.056***	0.055***	0.070***	0.056***	0.026***	0.125***	-0.014
	(0.009)	(0.011)	(0.010)	(0.008)	(0.008)	(0.010)	(0.011)
Trend after opening	-0.090***	-0.091***	-0.107***	-0.076***	-0.013	-0.195***	-0.007
	(0.012)	(0.015)	(0.013)	(0.011)	(0.010)	(0.014)	(0.017)
Bandwidth	14 days	14 days	14 days	14 days	14 days	14 days	14 days
R-squared	0.532	0.553	0.525	0.602	0.594	0.661	0.608
Observations	5,869	5,869	5,869	5,869	5,869	5,869	5,869

Notes: The dependent variables of the logarithm forms of AQI, and the six monitored air pollutants. The sample includes the observations in the four weeks surrounding each opening event. The control variables in the second panel include wind speed, precipitation, pressure, and dummies for holiday, hour of the day, heating period, weekday, and city fixed effects, and the interaction of weather and hour dummies. For the readability of the coefficients and standard errors, we divided the time trend by 100 (hour/100). Robust standard errors are reported in parentheses. ***, **, and * indicate that the coefficient is statistically significant at the 1%, 5%, or 10% significance level, respectively.

Table 4. Different Bandwidth

Panel A: One-month bandwidth

	Air quality index	PM2.5	PM10	Nitrogen oxides	Carbon monoxide	Sulfur dioxide	Ozone
Open	-0.206***	-0.260***	-0.175***	-0.059***	0.042***	-0.104***	0.115***
	(0.018)	(0.022)	(0.019)	(0.015)	(0.014)	(0.020)	(0.023)
Bandwidth	30 days	30 days	30 days	30 days	30 days	30 days	30 days
R-squared	0.460	0.477	0.458	0.582	0.540	0.622	0.584
Observations	12,372	12,372	12,372	12,372	12,372	12,372	12,372

Panel B: One-week bandwidth

	Air quality index	PM2.5	PM10	Nitrogen oxides	Carbon monoxide	Sulfur dioxide	Ozone
Open	-0.193***	-0.244***	-0.267***	-0.224***	-0.104***	-0.417***	0.042
	(0.034)	(0.042)	(0.039)	(0.029)	(0.026)	(0.037)	(0.044)
Bandwidth	7 days	7 days	7 days	7 days	7 days	7 days	7 days
R-squared	0.540	0.467	0.524	0.654	0.561	0.710	0.450
Observations	3,079	3,079	3,079	3,079	3,079	3,079	3,079

Notes: Regressions are the same as in Panel B of Table 3 except that the bandwidth is different. In Panel A, we use observations one month before and after the opening event. In Panel B, we use observations one week before and after the opening event. ***, **, and * indicate that the coefficient is statistically significant at the 1%, 5%, or 10% significance level, respectively.

Table 5. Alternative Time Trends

Panel A: Quadratic polynomial

	Air quality index	PM2.5	PM10	Nitrogen oxides	Carbon monoxide	Sulfur dioxide	Ozone
Open	-0.123***	-0.140***	-0.161***	-0.109***	-0.085***	-0.249***	0.044
	(0.039)	(0.047)	(0.044)	(0.032)	(0.029)	(0.042)	(0.050)
Bandwidth	14 days	14 days	14 days	14 days	14 days	14 days	14 days
R-squared	0.532	0.554	0.526	0.602	0.595	0.662	0.609
Observations	5,869	5,869	5,869	5,869	5,869	5,869	5,869

Panel B: Kernel regression

	Air quality index	PM2.5	PM10	Nitrogen oxides	Carbon monoxide	Sulfur dioxide	Ozone
Open	-0.112***	-0.120***	-0.145***	-0.124***	-0.061***	-0.217***	0.081**
	(0.028)	(0.034)	(0.033)	(0.024)	(0.021)	(0.031)	(0.035)
Bandwidth	14 days	14 days	14 days	14 days	14 days	14 days	14 days
Observations	5,869	5,869	5,869	5,869	5,869	5,869	5,869

Notes: The specification is the same as in Panel B of Table 3 except for the time trend. Panel A adds quadratic time trends to the linear time trends. Panel B uses a triangle kernel local regression to control for the time trend. ***, **, and * indicate that the coefficient is statistically significant at the 1%, 5%, or 10% significance level, respectively.

Table 6. Donut Regression Discontinuity

	Air quality index	PM2.5	PM10	Nitrogen oxides	Carbon monoxide	Sulfur dioxide	Ozone
Open	-0.197**	-0.521***	-0.047	-0.449***	-0.057	-0.245**	0.432**
	(0.100)	(0.125)	(0.113)	(0.101)	(0.071)	(0.122)	(0.177)
Bandwidth	14 days	14 days	14 days	14 days	14 days	14 days	14 days
R-squared	0.633	0.649	0.633	0.602	0.690	0.676	0.610
Observations	2,790	2,790	2,790	2,790	2,790	2,790	2,790

Notes: The specification and the bandwidth are the same as in Panel B of Table 3. The sample is different. The observations that are one week before and one week after the day of a subway opening are excluded. ***, **, and * indicate that the coefficient is statistically significant at the 1%, 5%, or 10% significance level, respectively.

Table 7. Control for the Lagged Dependent Variable

	Air quality index	PM2.5	PM10	Nitrogen oxides	Carbon monoxide	Sulfur dioxide	Ozone
Open	-0.013*	-0.015*	-0.017*	-0.030**	-0.020*	-0.054***	0.035
	(0.007)	(0.009)	(0.009)	(0.015)	(0.011)	(0.020)	(0.024)
First lag	1.090***	1.162***	1.051***	0.729***	0.656***	0.665***	0.617***
	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.014)
Second lag	-0.084***	-0.168***	-0.030	0.118***	0.204***	0.143***	0.181***
	(0.021)	(0.022)	(0.021)	(0.020)	(0.018)	(0.018)	(0.017)
Third lag	-0.028	-0.030	-0.108***	0.013	0.032*	0.033*	0.075***
	(0.021)	(0.022)	(0.020)	(0.020)	(0.018)	(0.018)	(0.017)
Fourth lag	-0.023	-0.005	0.033**	-0.009	-0.008	0.018	-0.036**
	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)
Total effect	-0.06907	-0.08383	-0.08573	-0.10336	-0.06793	-0.1747	0.110351
Bandwidth	14 days	14 days	14 days	14 days	14 days	14 days	14 days
R-squared	0.970	0.975	0.961	0.878	0.894	0.887	0.863
Observations	4,969	4,969	4,969	4,969	4,969	4,969	4,969

Notes: This table includes lags of one through four hours of the dependent variable. The total effect of subway opening on air quality is calculated using the method in Henderson (1996). ***, **, and * indicate that the coefficient is statistically significant at the 1%, 5%, or 10% significance level, respectively.

Table 8. Interaction of City Fixed Effects with Other Controls

	Air quality index	PM2.5	PM10	Nitrogen oxides	Carbon monoxide	Sulfur dioxide	Ozone
Open	-0.198***	-0.236***	-0.219***	-0.140***	-0.021	-0.273***	-0.008
	(0.026)	(0.031)	(0.029)	(0.023)	(0.021)	(0.031)	(0.042)
Bandwidth	14 days	14 days	14 days	14 days	14 days	14 days	14 days
R-squared	0.683	0.705	0.670	0.692	0.688	0.727	0.651
Observations	5,869	5,869	5,869	5,869	5,869	5,869	5,869

Notes: The specification and the bandwidth is the same as in Panel B of Table 3, except the additional interactions of the weather variables with city fixed effects. ***, **, and * indicate that the coefficient is statistically significant at the 1%, 5%, or 10% significance level, respectively.

Table 9. Effects of Subway Opening by Time of Day

Panel A: Night time

	Air quality index	PM2.5	PM10	Nitrogen oxides	Carbon monoxide	Sulfur dioxide	Ozone
Open	-0.100	-0.137	-0.093	-0.080	0.003	0.013	0.137
	(0.079)	(0.095)	(0.088)	(0.074)	(0.054)	(0.093)	(0.102)
Bandwidth	14 days	14 days	14 days	14 days	14 days	14 days	14 days
R-squared	0.531	0.531	0.511	0.507	0.593	0.606	0.531
Observations	739	739	739	739	739	739	739

Panel B: Peak hours

	Air quality index	PM2.5	PM10	Nitrogen oxides	Carbon monoxide	Sulfur dioxide	Ozone
Open	-0.225***	-0.262***	-0.258***	-0.153***	-0.107*	-0.158	0.198*
	(0.084)	(0.099)	(0.096)	(0.056)	(0.055)	(0.105)	(0.115)
Bandwidth	14 days	14 days	14 days	14 days	14 days	14 days	14 days
R-squared	0.512	0.515	0.499	0.545	0.616	0.578	0.509
Observations	738	738	738	738	738	738	738

Panel C: Non-peak daytime hours

	Air quality index	PM2.5	PM10	Nitrogen oxides	Carbon monoxide	Sulfur dioxide	Ozone
Open	-0.076	-0.061	-0.105	-0.127**	-0.119*	-0.249***	0.012
	(0.081)	(0.099)	(0.091)	(0.061)	(0.071)	(0.091)	(0.075)
Bandwidth	14 days	14 days	14 days	14 days	14 days	14 days	14 days
R-squared	0.553	0.569	0.551	0.606	0.508	0.692	0.688
Observations	739	739	739	739	739	739	739

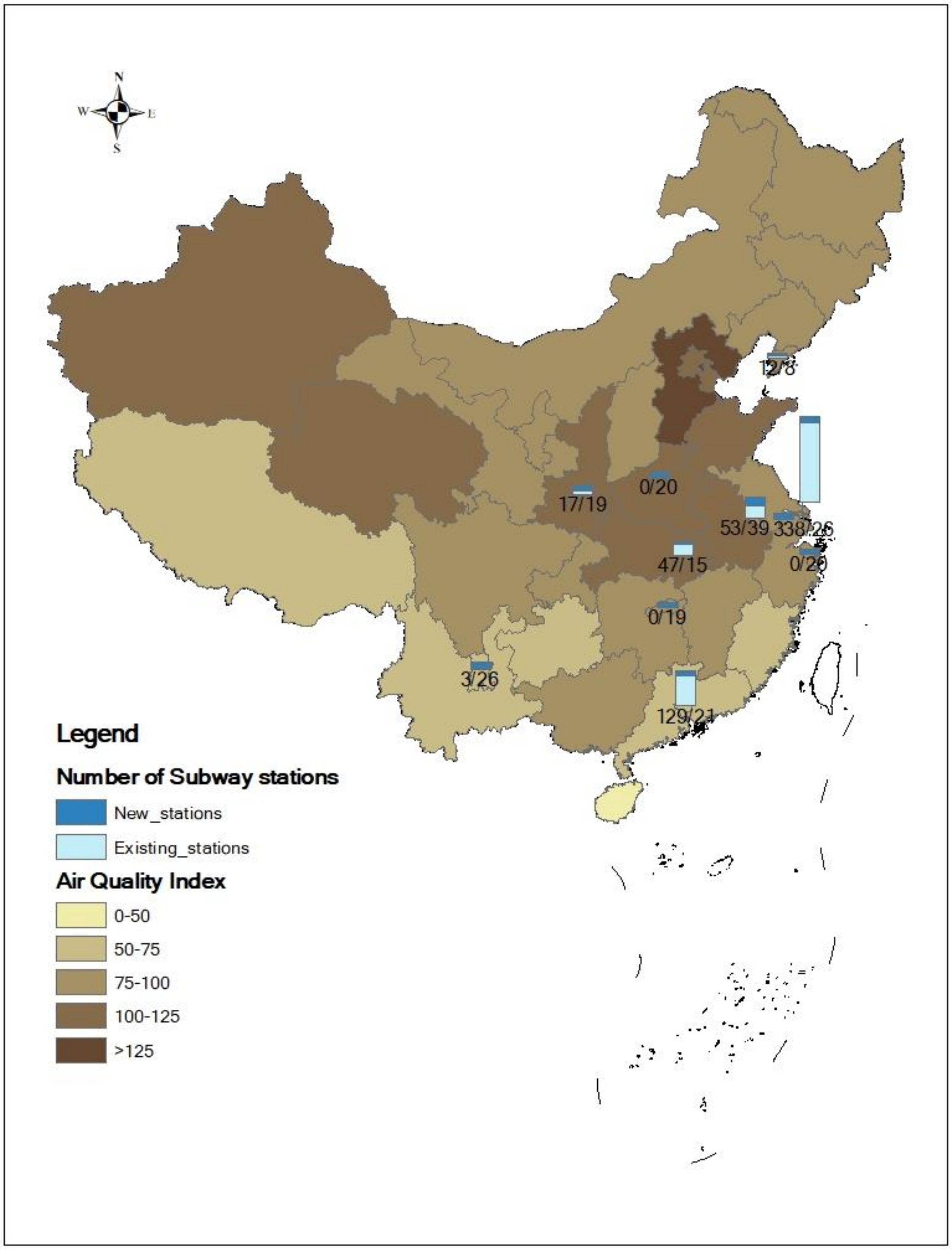
Notes: Each panel reports the coefficient of the opening dummy using a subsample of time periods in a day. Data used are observations from 1 a.m. to 3 a.m. in Panel A, observations from 6 a.m. to 8.a.m in Panel B, and observations from 10 a.m. to 12 a.m. in Panel C. Regressions are otherwise the same as in Panel B of Table 3. ***, **, and * indicate that the coefficient is statistically significant at the 1%, 5%, or 10% significance level, respectively.

Table 10. Heterogeneity in the Effects across Cities

	Air quality index	PM2.5	PM10	Nitrogen oxides	Carbon monoxide	Sulfur dioxide
Panel A: Average income per capita						
Open*log(income)	0.636***	0.812***	0.681***	0.638***	0.425***	0.381***
	(0.068)	(0.084)	(0.074)	(0.062)	(0.053)	(0.080)
Open	-6.797***	-8.660***	-7.291***	-6.789***	-4.494***	-4.123***
	(0.711)	(0.875)	(0.780)	(0.647)	(0.558)	(0.841)
Log(income)	-0.508***	-0.620***	-0.453***	-0.671***	-0.385***	-0.050
	(0.070)	(0.086)	(0.076)	(0.063)	(0.055)	(0.082)
Panel B: Population density						
Open*log(density)	-0.097***	-0.172***	-0.035	0.067***	-0.107***	-0.051**
	(0.019)	(0.024)	(0.021)	(0.018)	(0.015)	(0.023)
Open	0.577***	1.107***	0.111	-0.580***	0.738***	0.232
	(0.142)	(0.174)	(0.156)	(0.130)	(0.111)	(0.167)
Log(density)	0.331***	0.526***	0.305***	-0.131	0.146**	-0.010
	(0.093)	(0.115)	(0.103)	(0.086)	(0.073)	(0.110)
Panel C: Whether new line is the first in the system						
Open*first line	-0.237***	-0.250***	-0.272***	-0.327***	-0.100***	-0.074***
	(0.023)	(0.029)	(0.025)	(0.021)	(0.018)	(0.028)
Open	-0.021	-0.029	-0.021	0.058**	0.009	-0.101***
	(0.028)	(0.035)	(0.031)	(0.025)	(0.022)	(0.033)
First line	0.598	0.791	-1.305**	-4.884***	-1.543***	-2.955***
	(0.492)	(0.607)	(0.539)	(0.444)	(0.387)	(0.583)
Panel D: Number of existing stations						
Open*stations	0.001***	0.001***	0.001***	0.002***	0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Open	-0.172***	-0.186***	-0.195***	-0.191***	-0.064***	-0.114***
	(0.027)	(0.033)	(0.029)	(0.024)	(0.021)	(0.032)
Number of	0.002***	0.002***	0.002***	0.001***	-0.000	0.003***
existing stations	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

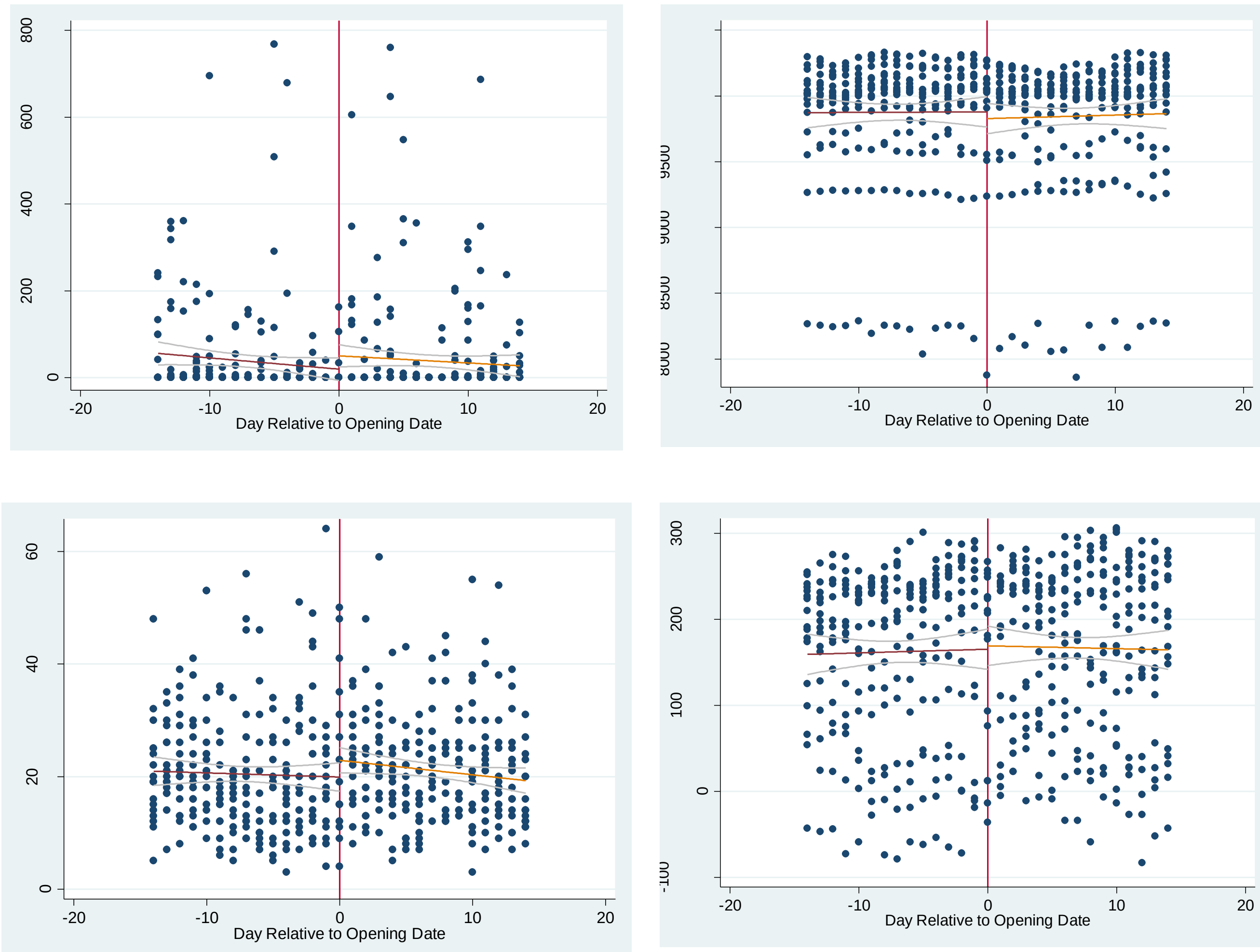
Notes: Regressions are the same as in Panel B of Table 3, except that the regressions also include the interaction of the opening dummy with the variable indicated in the row headings. ***, **, and * indicate that the coefficient is statistically significant at the 1%, 5%, or 10% significance level, respectively.

Figure 1. Cities with New Subway Stations in 2013 and 2014



Notes: This figure shows the air quality index (AQI) in each province in China during 2013 and 2014. The darker the color is, the worse the air quality. The dark blue and light blue bars show the number of existing and new subway stations, respectively, in our sample. The numbers below the bars are the number of existing stations and the number of new stations.

Figure 2 Weather Conditions Before and After Subway Opening Days

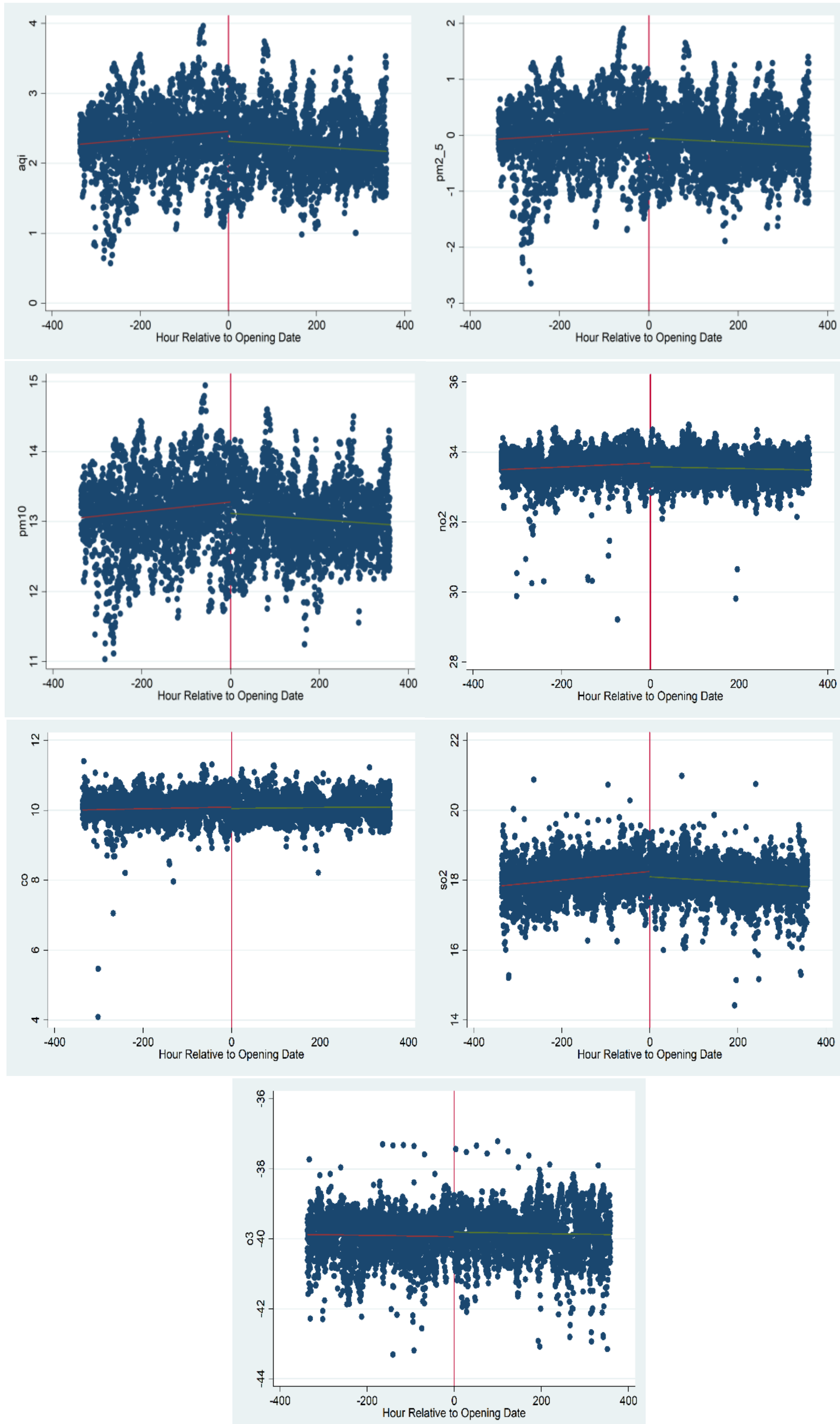


Notes: The four panels depict the wind speed, pressure, precipitation and temperature of the cities. The sample includes the observations two weeks before and after the subway openings. The lines are fitted by linear regressions separately for the days before and after the openings. The grey lines show the 95% confidence intervals. In the pressure chart, most cities are above the fitted line. The lowest dots are Kunming, which is located on a plateau, and therefore has much lower pressure than other cities. The estimation results in the paper are robust to excluding Kunming.

Figure 3. Pollution Levels in Cities with Subway Station Openings in 2013 and 2014

Notes: The sample includes observations from January 2013 through October 2014 for all cities listed in Table 1, except for the two excluded cities. The red vertical lines denote the opening of a subway line. The red and green lines are fitted by kernel regressions separately for observations before and after the opening.

Figure 4. Pollution Residuals



Notes: The figure plots the residuals of the indicated pollutant or air quality index after partialling out the independent variables in Equation (1) other than the opening dummy. The red and green lines are fitted for the residuals in a linear time trend.