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Abstract

Using a unique city-level panel on the daily air pollution index (API) and fine-scale meteorological data from 2009 to 2013 in China, we examine the existence and the magnitude of spatial spillover effects of urban air pollution in Chinese cities. Our spatial analysis results indicate that (i): there exist spatial spillover effects of air pollution in China: a city's average API is expected to increase by 0.40-0.51 if the average API in its surrounding cities increases by one unit, depending on model specifications; (ii) an increase in gasoline price can effectively improve urban air quality; (iii) high levels of precipitation and strong winds can mitigate air pollution, while the temperature effects on air quality vary by time of day; and (iv) without controlling for spatial spillovers of air pollution across regions, coefficient estimates of explanatory variables will be biased. Our findings suggest that pollution control policies must be coordinated among cities and provinces to effectively abate urban air pollution.

Key Words: air pollution, wind, spatial spillover, SDPD model, China

JL Codes: Q53, C23

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1. Introduction

China's poor air quality has put the country in the world's spotlight. In 2011, the number of days exceeding the World Health Organization air quality guidelines was greater than 250 days in many Chinese cities (Cheng et al. 2013). International media has described air quality in China reaching levels that are "hazardous to human health" (BBC 2013). Air pollution has resulted in a reduction in average life expectancy of about 5.5 years for residents in North China (Chen et al. 2013a), and is a leading cause of premature death (Chen et al. 2013b, Yang et al. 2013). Air pollution is also believed to have contributed to China's growing social unrest in recent years (Bloomberg 2013).

To find solutions to China's air pollution problem, numerous efforts have been made to identify key sources of air pollution in Chinese cities, with a particular focus on the nation's capital city, Beijing (Guo et al. 2014, Zhang et al. 2013). However, due to the differences in data and research methods used, empirical findings about factors contributing to air pollution are mixed. For instance, using data collected from an urban site in Beijing between April 2009 and January 2010, Zhang et al. (2013) showed that industrial pollution and secondary inorganic aerosol formation were the major sources of the city's air pollution, while traffic emissions played only an insignificant role. Based on the data collected at Peking University located in northwestern Beijing from September to November 2013, Guo et al. (2014) concluded that nitrogen oxides (NOx) from local transportation and sulfur dioxide (SO_2) from regional industrial sources were the main sources of air pollution in Beijing.

Several studies have attributed Beijing's poor air quality to neighboring cities/provinces. Using integrated simulation models, Streets et al. (2007) and Chen et al. (2007) estimated that

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neighboring cities can have a large influence on Beijing's air quality. Based on observed ambient concentrations of ozone (O_3), carbon monoxide (CO), SO_2, and NOx, Lin et al. (2009) and Wang et al. (2010) observed a strong correlation between Beijing's air pollution concentrations and air pollution concentrations in its neighboring areas.

Identifying primary sources of air pollution is the critical first step before efficient abatement strategies can be developed to mitigate urban air pollution. If air pollutants are generated mostly from local sources, such as traffic emissions and/or coal burning, an effective pollution abatement strategy should target these local sources. On the other hand, if air pollutants in a region are found to come primarily from its neighboring areas, collective efforts for regional air pollution abatement would be called for. With the lack of rigorous empirical analysis, China's air pollution control strategies have been shown to perform quite poorly. At present, the common strategy adopted by many Chinese cities to improve air quality is to relocate large-scale and heavily polluting factories to suburbs and to neighboring provinces. For instance, to host the 2008 Olympic Games, China relocated several large, heavily polluting firms to Beijing's neighboring cities as one of a series of actions to improve Beijing's air quality (Chen et al. 2013). However, Guo et al. (2014) showed that relocating polluting firms is a poor pollution abatement strategy, because Beijing's neighboring cities/provinces contributed significantly to ambient air pollution concentrations in Beijing after the Olympic Games. Therefore, to move China's environmental policy forward, there is an urgent need for more rigorous studies with high quality data to examine the true causes of urban air pollution in China.

Incorporating factors from both local and neighboring sources, this paper examines whether there exist spatial spillover effects of air pollution in Chinese cities, and determines the magnitudes of various local and neighboring factors in influencing ambient air pollution concentrations in Chinese cities. To conduct the analysis, we compile a unique daily city-level panel that includes 119 major Chinese cities from 2009 to 2013. We use the officially reported air pollution index (API) by China's Ministry of Environmental Protection (MEP) as the indicator for air quality. Local factors affecting a city's air quality include temporally lagged API, which represents the city's air quality on previous days; weather conditions, such as temperature, precipitation, solar radiation, and wind speed; and fuel prices, to control for air pollution from vehicle emissions. Air pollution from neighboring areas is measured using a spatially-weighted API in neighboring cities that depends on physical distance between cities as well as on wind direction and wind speed in neighboring cities.

We develop a spatial dynamic panel data (SDPD) model to assess the impacts of various local and neighboring factors on city-level air quality. In addition to the explanatory variables mentioned above, to minimize the potential estimation bias originating from omitted variables, we augment the model using city-year-season fixed effects (FE). The high dimension FE captures a wide range of unobserved factors within a city-year-season that may affect city-average air quality, such as seasonal coal burning for heat and power generation, farmers' seasonal illicit burning of crop residues, dust generated from occasional sand storms and/or from the construction of new buildings and roads, number of vehicles, and perhaps others. A first differencing type identification strategy with instrumental variables circumvents these potential confounders.

We have four main findings. First, we find strong evidence of the existence of spatial spillover effects of urban air pollution in China. Specifically, a one-unit increase in API in surrounding cities will raise a city's API by about 0.40-0.51, holding all else the same. Second, coefficient estimates of explanatory variables will be biased if the spatial weights matrix does not control for wind direction and wind speed in neighboring cities. Third, we find that an increase in gasoline price can effectively reduce urban air pollution, possibly by reducing fuel consumption. Lastly, consistent with the existing studies on atmospheric pollution (Sillman 1999, Tai et al. 2010), high levels of precipitation and strong winds can mitigate air pollution, while the temperature effects on air pollution vary by time during a day.

This paper is not the only attempt to investigate the existence of spatial spillover effects of urban air pollution in China. As mentioned above, several studies have discovered that Beijing's neighboring Hebei and Shandong provinces and the Tianjin Municipality contributed significantly to ambient air pollution concentrations in Beijing (Chen et al. 2007, Lin et al. 2009, Streets et al. 2007, Wang et al. 2010). We improve on this literature in three major aspects.

First, our dataset is unique and comprehensive. The existing studies that have examined the spatial spillover effects of air pollution in China primarily focus on Beijing and the data used in these studies span only a very short period of time (see Guo et al. 2014, Zhang et al. 2013). In contrast, our city-level panel includes 119 major Chinese cities and contains detailed information on daily air quality and meteorological conditions for these cities during the period 2009-2013. The unique data structure enables us to construct city-year-season FE which can minimize the potential estimation bias originating from omitted variables. It also allows us to examine whether spatial spillover effects of air pollution differ by region.

Second, our spatial econometric model is novel. When applying spatial econometric models to solve individual problems, many empirical studies specify spatial weights matrices based on either geographical criteria or economic dependence between different regions/sectors.

These studies typically assume that spatial weights matrices are exogenous and time-invariant (see Anselin and Bera 1998, Chow et al. 1994, Won Kim et al. 2003), thus ignoring that under certain circumstances spatial dependence of two regions/sectors is likely to change over time. In this paper, we allow our spatial weights matrix to change daily according to wind direction and wind speed, which is expected to increase the precision of our coefficient estimates.

Third, although this paper focuses on air pollution, our research contributes to a broader literature on the design of efficient environmental policies to control transboundary pollution. Several studies in the U.S. have documented negative spatial externalities of agricultural runoffs (Goetz and Zilberman 2000, Griffin and Bromley 1982), and analyzed optimal management strategies for groundwater pumping (Brozović et al. 2010, Chakravorty and Umetsu 2003, Kuwayama and Brozović 2013, Pfeiffer and Lin 2012). In line with these studies, our empirical findings also suggest that collective efforts, such as joint prevention and control between adjacent cities/provinces, are needed to control for transboundary air and water pollution.

The rest of the paper is organized as follows. Section 2 discusses various factors that may affect urban air quality. Section 3 presents our empirical model and identification strategy. Section 4 describes data sources and summary statistics. Section 5 presents results, while Section 6 concludes.

2. Sources of Urban Air Pollution in China

Based on the origins of air pollutants, we categorize the contributing factors of air pollution into local factors and neighboring factors. Local factors include city-specific meteorological conditions (such as temperature, precipitation, and wind) (Chan and Yao 2008), economic factors (such as industrial structure, urbanization, energy use, and number of vehicles) (Zhang et al. 2011), and city-specific environment protective measures. Neighboring factors refer to air pollutants transported from other regions by the passage of wind. In this section, we will discuss each of these factors.

2.1 Local Factors

2.1.1 Meteorological Conditions

Meteorological conditions, such as precipitation, wind, temperature, and solar radiation, have been well recognized as important factors affecting the degree of a city's air quality. Particulate matter (PM) is reported to be the major air pollutant in Chinese cities (Chan and Yao 2008). Precipitation can increase the weight of PM floated in the air and cause the particles to fall. Strong winds can facilitate atmospheric dispersion and thus can reduce the concentration of ambient air pollutants. Therefore, precipitation and strong winds are expected to improve a city's air quality.

While wind affects the horizontal movement of air pollutants, the literature on atmospheric pollution suggests that temperature influences the vertical movement of air pollutants (Arya 1998). When ground temperature increases, warm air tends to rise, expand, and move to areas with cold air, which causes air to move vertically. The vertical movement of air as a result of temperature rise can move air pollutants away from the ground level, and thus reduce ground-level air pollution. Existing studies in atmospheric pollution also find that high temperature combined with sunshine can stimulate the formation of ozone, which is another major source of urban air pollution. Cities with high temperature generally experience high levels of ozone (Sillman 1999).

2.1.2 Vehicle Emissions

Vehicle emissions are the primary source of urban air pollution, especially in developing countries, including China.[1] China's private car sector has experienced explosive growth during the past decade. The number of privately owned vehicles in Chinese cities increased from 7.71 million in 2001 to 88.39 million in 2012, with an average annual rate of growth of nearly 25% (NBS 2001-2012). A recent emission inventory indicates that, although contributions of vehicles to urban air pollution differ by region, vehicles are responsible for about 70% of the CO and hydrocarbon and nearly 90% of the NO_x and PM in Chinese cities (Ministry of Environmental Protection of China 2013).

China has implemented four different regulations to control vehicle emissions during the past decade. Regulations for light vehicles include national I (initiated in 1999 and effective in 2001), national II (effective in 2004), national III (effective in 2007) and national IV (effective in 2010), which are equivalent to Euro I, II, III, and IV, respectively. Regulations for heavy-duty vehicles have also been implemented, with one or two years lag compared to that for light vehicles.

[1] According to the United Nations Environment Programme, over 90% of urban air pollution in major cities, especially in developing countries, can be attributed to vehicle emissions; see www.unep.org/urban environment/Issues/urban air.asp

2.1.3 Coal Burning for Power and Heat Generation

Another main source of air pollution in Chinese cities is coal burning for winter heating of homes and offices. Currently, coal is the primary energy source consumed in China, accounting for about 66% of China's domestic energy consumption. Burning coal in boilers is associated with the release of air pollutants, such as SO_2, NO_x, and PM. To reduce air pollution from the combustion of coal in coal-fired power plants, China has implemented several regulatory policies that require coal power plants to install and operate SO_2 scrubbers and dust-removing technologies (Xu et al. 2009, Zhao and Gallagher 2007).

2.1.4 Other Local Factors

Other local factors include air pollution stemming from industrialization and urbanization, and dust from burning agricultural biomass and from occasional sand storms. China's rapid development of industrialization and urbanization may have contributed significantly to urban air pollution. Many industrial sectors in China, such as coal mining, cement, and paper and chemical production, still depend on inefficient or polluting technology with low energy efficiency (Liu and Diamond 2005). Construction of new buildings and roads in many Chinese cities in the past decade as a result of the rapid expansion of urbanization has also generated a significant amount of dust, which is believed to be responsible for about 14.3% of the PM in Beijing during the period 2012-2013.[2] Moreover, farmers' seasonal illicit burning of agricultural biomass and occasional dust storms have also negatively affected air quality of many Chinese cities.

Central and local governments have undertaken various efforts to improve urban air quality, including closing heavily polluting facilities, regulating contents of gasoline and diesel, and saving energy during construction. Driving restrictions have been introduced by some Chinese cities. For instance, Viard and Fu (forthcoming) found that driving restrictions in Beijing significantly improved the city's air quality.

A city's air quality also depends on its own previous air quality. Holding all other factors constant, if a city experiences a high level of air pollution on a given day, its air quality on the following day is expected to be poor.

[2] The Chinese-language version of the website is available at: http://www.bjepb.gov.cn/bjepb/323474/331443/331937/333896/396191/index.html

2.2 Neighboring Factors

Wind can transport air pollutants from one region to other regions. Thus, a city's air quality is expected to be influenced by air pollutants transported from upwind cities. Guo et al. (2014) discovered that pollutants from industrial sectors located in Beijing's neighboring provinces contributed substantially to PM formation in Beijing. Kallos et al. (1998) found evidence that wind blew polluted air from southern Europe to Africa. The U.S. Environmental Protection Agency (EPA) also believes that international transport of air pollution has a significant negative impact on U.S. air quality.[3]

3. Empirical Strategy

3.1 Model Specification

Following the theoretical framework, a city's daily air quality depends on its own previous air condition, air quality in surrounding cities, and its socioeconomic and meteorological characteristics. To include both spatial and temporal aspects of urban air pollution, we estimate a spatial autoregressive (or spatial lag) model in a dynamic panel setting (spatial dynamic panel model, SDPD).[4] This model considers urban air pollution with both temporal and spatial correlations.

Formally, we estimate

$$API_{i,ysd} = \alpha + \tau API_{i,ysd-1} + \rho \sum_{j\neq i}^{J} \omega_{ij,ysd} API_{j,ysd} + x_{i,ysd}\beta + \mu_{i,ys} + \varepsilon_{i,ysd} \quad (1)$$

where $API_{i,ysd}(API_{j,ysd})$ is a measure of city-average air pollution for city i (j) on day d in season s of year y, and $\omega_{ij,ysd}$ is the weight assigned to city *j* by city *i* on day *d* in season *s* of year y. $x_{i,\text{ysd}}$ is a vector of covariates describing conditions in city *i* on day *d* in season *s* of year *y*, including weather variables, fuel prices (this variable is used to control for emissions from vehicle miles travelled), and dummy variables for weekends and national holidays. Weather variables include daily precipitation, solar radiation, maximum temperature (T_{max}), minimum temperature (T_{min}) and average wind speed. Because nearly all private vehicles in China are powered with gasoline, in the empirical analysis we use gasoline price to control for the effects

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[3] http://www.epa.gov/airtrends/2010/report/intltransport.pdf

[4] There is a growing literature studying the SDPD model; see Elhorst (2001) and Lee and Yu (2010) and (2014) for a theoretical overview.

of vehicle emissions on city-average API. An increase in gasoline price is expected to reduce vehicle miles travelled and thus total fuel consumption,[5] which in turn may improve urban air quality. $\mu_{i,ys}$ denotes the city-year-season fixed effects that can capture a wide range of unobserved factors that are common to a city in a given year and season, such as seasonal coal consumption (in particular in North China, where coal is used for winter home and office heating); farmers' seasonal illicit burning of crop residues; construction of buildings, subways and new roads; and policies implemented by different levels of government in a bid to reduce air pollution. $\varepsilon_{i,ysd}$ are the idiosyncratic error terms.

The atmospheric pollution literature suggests that there exists some natural dilution of air pollution (Mayer 1999). Thus, we make two assumptions to simplify model (1). First, we assume that the temporal dependency of air pollution for a city exists only between day *d* and day *d-1*. Second, a city's air quality on a given day is assumed to be affected by the air pollution concentrations in surrounding cities on the same day. To examine the robustness of our results to the second assumption, we will consider one model specification that includes the one-day lag in $\sum_{j\neq i}^{J} \omega_{ij,ysd}\, API_{j,ysd}$ as an additional explanatory variable.

In terms of parameters, τ captures the temporal dependency of air pollution for city *i* between day *d* and day *d-1*; ρ represents the effects of the air pollution in surrounding cities on city *i's* air quality. This parameter also measures the causal effect of the weighted level of air pollution of one city's neighbors on its own air pollution. Effects of other covariates on city *i*'s air pollution are reflected by β.

3.2 Weighting Scheme

To estimate (1), the spatial weights matrix ($\omega_{ij,ysd}$) must be specified. Given the large-scale movement of air within immediate vicinities, it is not surprising to observe significant interaction of air pollution levels across space (Kanaroglou et al. 2013, Zhang et al. 2011). Atmospheric research has also emphasized the importance of wind speed and wind direction in dispersing air pollutants across regions (Chan and Yao 2008, Nieuwenhuijsen et al. 2007). In light of this, our preferred weighting scheme (2) uses three sources of information.

[5] The effects of fuel price on vehicle miles travelled have been well studied; see Greene (1992) and Wang and Chen (2014).

$$\omega_{ij,ysd} = \begin{Bmatrix} \frac{1}{d_{i,j}} & if\ g_{i,j} = wd_{j,ysd} \\ 0 & otherwise \end{Bmatrix} \quad (2)$$

The first source of information is the geographical distance between the centroid of city *i* and the centroid of city *j*, represented by $d_{i,j}$. We assign positive weights to cities if they are geographically close to city *i*, and assign zero weights to other cities. In the baseline, we set the distance cutoff at 500 kilometers, i.e., $d_{i,j} \leq 500$ kilometers, and the value of the weights assigned equals the inverse geographical distance between city *i* and city *j*, $\frac{1}{d_{i,j}}$. The sensitivity of our results using other distance cutoffs will be tested in the robustness check section.

The second source of information is the geographical location of city *j* relative to city *i* (denoted by $g_{i,j}$) and the wind direction in city *j* on day *d* in season *s* of year *y* (denoted by $wd_{j,ysd}$). In addition to geographical distance, spatial interaction of airborne pollutants is most likely to occur if there is sufficient air flow. Unlike the time-invariant geographical contiguity, wind direction changes fairly frequently and carries rich time-varying information on transboundary air pollution. Therefore, we assign a positive weight to city *j* if there is wind blowing from city *j* toward city *i*, i.e., $g_{i,j} = wd_{j,ysd}$. For instance, if city *j* is located southwest of city *i*, air pollution in city *j* on day *d* in season *s* of year *y* can affect city *i*'s air quality on the same day if and only if city *j* has a southwest wind blowing on that day. We use 16 cardinal directions to represent $g_{i,j}$ and $wd_{j,ysd}$. It is worth pointing out that the spatial weights matrix changes on a daily basis, like other variables in the regression.

The third source of information is wind speed. The speed of wind determines how long it can take air pollutants to travel from the origin city *j* to the destination city *i*. This information becomes crucial when we want to separately identify temporal and spatial dependency of urban air pollution. If wind speed in city *j* is not large and it takes more than one day to transport air pollutants to city *i*, there would be measurement errors if we constructed the spatial weights matrix without considering wind speed. That is because the one-day lagged dependent variable, $API_{i,ysd-1}$, captures not only temporal variations, but also the spatial autocorrelation due to the "late arrival" of air pollutants from surrounding areas.

Therefore, we assign a positive weight to city *j* if: (*i*) city *i* and city *j* are geographically close; (*ii*) there is wind blowing from city *j* to city *i* on day *d*; and (*iii*) wind speed in city *j* is sufficiently large so that airborne pollutants can be carried from city *j* to city *i* within one day.[6]

3.3 Identification

To obtain consistent estimates of τ and ρ, we need to confront the following three identification issues: (*i*) correlations between $API_{i,ysd-1}$ and the error terms after the usual within (demeaning) or first-differencing transformation to remove the unobserved heterogeneity (Baltagi 2008); (*ii*) endogeneity of the spatially lagged variables due to the simultaneous determination of regional air pollution levels (Anselin 2002); and (*iii*) potential endogeneity of other control variables.

To circumvent the three issues, we use the system Generalized Method of Moments (GMM) estimator, which is a popular identification strategy for the stable SDPD model with fixed effects (Blundell and Bond 1998, Lee and Yu 2014). In particular, the approach involves, first, taking time differences to eliminate both the constant term and the city-year-season FE in Eq. (1), and, then, using lagged levels and differences as instruments for the exogenous and endogenous variables in the first-differences (Blundell and Bond 1998). System GMM estimation has been shown to offer increased efficiency and less finite sample bias as compared to the difference GMM estimation and (quasi) maximum likelihood estimation (MLE), especially when the data are persistent (Blundell and Bond 1998, Elhorst 2012).[7]

Given the high dimensionality of the fixed effects, first differencing is powerful at removing cofounding variables. The city-year-season FE can capture all the city-year-season variations in unobservables affecting local air quality, such as coal consumption, farmers' illicit

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[6] As in the majority of the literature on spatial models, the choice of weighting scheme is a bit *ad hoc*. While we consider alternative weighting schemes in our sensitivity analysis, a sizable body of air pollution research supports the use of geographical and atmospheric variables (Kanaroglou et al. 2013, Zhang et al. 2011). If the spatial weights matrix is mis-specified, this would likely attenuate our estimates and result in a lower bound for the estimation of the contribution to local air pollution from surrounding areas. However, given the fairly consistent evidence suggesting spatial correlation, we would not be overly concerned about this issue.

[7] Another leading procedure for the SDPD model is the (quasi) maximum likelihood estimation (MLE), which is unfortunately not applicable in our particular context. One reason is that we are dealing with a time-varying weight matrix once the wind direction and speed information are used together. The MLE or Quasi-MLE practice requires the weight variable to be constant within each panel unit (Lee and Yu 2014). Another reason is that the MLE procedure is very computationally demanding. Given the high dimensionality of our city-year-season fixed effects, the task is simply beyond our computation power (Elhorst 2012, Lee and Yu 2014, Lee and Yu 2010).

burning of crop residues, and construction of buildings, subways and new roads. Therefore, this approach helps us deal with the omitted variable issue that plagues the existing empirical air pollution studies.

In the baseline analysis, we treat gasoline price and weather variables as potential endogenous variables, because they could be affected by pollution levels (Barnett and Knibbs 2014). We instrument these variables using suitable lags. However, we would not be overly concerned about the possibility of reverse causation, because China's domestic fuel prices are highly regulated (Yang et al. 2012). The baseline price of fuel in China is set by the National Development and Reform Commission (NDRC). State-owned retailers (Sinopec and PetroChina) can adjust retail fuel prices within a tight 8% up or down band of the baseline price.[8] Although China has been slowly revising the fuel pricing policy to better reflect the international price of crude oil, the pricing mechanism designed by NDRC is not market-driven and mostly aims at reducing shocks to China's macro-economy (Tan and Wolak 2009).

Weather variables are also instrumented because of the possible autoregressive disturbances. The spatial correlation among disturbances can occur if cities within immediate proximity are affected by a common climate shock. If the city-year-season FE cannot entirely absorb this unobserved shock, the covariance between weather variables and the error terms will not be zero.

We instrument these potential endogenous variables using their lagged levels dated *d-2* to *d-3* and the first difference dated *d-1*. The reported standard errors are estimated via two steps, with Windmeijer finite-sample correction, to adjust the downward bias in two-step estimation while improving efficiency. The standard errors are consistent in the presence of any pattern of heteroskedasticity and autocorrelation within panels. To reduce the danger of instrument proliferation in system GMM, we have also tested the sensitivity of our results using a smaller number of instruments.

4. Data

We compile the data from three major sources. This section describes each data source and reports summary statistics.

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[8] http://www.theicct.org/blogs/staff/contextualizing-chinas-fuel-pricing-announcement

4.1 API Data

We obtain daily API for 119 major cities in China during the period 2009-2013 from the MEP.[9] Figure 1 shows that the cities included in our sample are widely distributed across China. API is a composite index of SO_2, NO_2, and particulate matter with a diameter of 10 micrometers or smaller (PM_{10}).[10] The MEP uses a nonlinear transformation to convert concentrations of these air pollutants into API that ranges between 0 and 500. If average API on a day exceeds 500, then it is capped at 500. If average API is below 100, then the day is defined as a "blue sky" day.

At present, the number of "blue sky" days is used as a measure for environmental performance of local officials by the central government. Because of this self-reporting, concerns have been raised regarding the validity of the officially reported API data. Wang et al. (2009) collected PM samples at Peking University located in Northwestern Beijing for six weeks in 2008. They found the self-measured PM_{10} concentrations were about 30% higher than that reported by the Beijing Environmental Protection Bureau. Using daily air pollution concentrations during the period 2001-2010, Ghanem and Zhang (2014) showed that many Chinese cities may have manipulated the official API data, especially for API scores around 100. Chen et al. (2012) confirmed such API discontinuity around 100, but showed a significant correlation of API with another commonly used air pollution measure, namely Aerosol Optical Depth (AOD) from NASA satellites. Therefore, although the official API data are subject to manipulation, they are the best available measurement of air pollution levels in urban China, and still provide useful information about air pollution in Chinese cities.

4.2 Evidence on the Spatial Correlations of API

We select four representative cities in China and present the co-movement of air pollution levels between these cities and their neighboring cities in Figure 2. The four major cities are located in different areas in China, including Beijing (located in northern China), Shanghai (located in the Yangtze River Delta in eastern China), Shenzhen (located in the Pearl River Delta in southern China), and Chengdu (a major city located in western China). We plot daily API in 2012 for the four cities and their three closest neighboring cities. As shown in

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[9] http://datacenter.mep.gov.cn/

[10] For a comprehensive discussion about the construction of API, see http://www.aqhi.gov.hk/pdf/related_websites/APIreview_report.pdf

Figure 2, we find that there exist positive and significant correlations between the API in these cities and the API in their neighboring cities. Specifically, the correlation coefficients between Beijing and its three surrounding cities are 0.69, 0.39 and 0.55, respectively. The correlation coefficients between Shanghai and its three neighboring cities are larger, at 0.65, 0.82, and 0.68, respectively. API correlations for Shenzhen and Chengdu and their neighboring cities are also large and statistically significant.

4.3 Weather and Gasoline Price Data

We gather weather data from the China Meteorological Data Sharing Service System (CMDSSS), which records daily minimum, maximum and average temperature (T_{min}, T_{max}, and T_{ave}), precipitation, solar radiation, average wind speed, and wind direction for 820 weather stations in China. The dataset spans from 2009 to 2013. The weather data also contain exact coordinates of weather stations, enabling us to match weather data with our API data. Each of the cities included in the sample has at least one weather station. For cities with several weather stations, we construct weather variables by taking a simple average of these weather variables across these stations.

Figure 3 shows the wind rose plots for Beijing, Shanghai, Shenzhen, and Chengdu in 2012. We find that, although wind directions in the four cities exhibit seasonal patterns, they have significant variations within a season. This finding suggests that it is important to control daily wind directions when constructing the spatial weights matrix in the empirical analysis in order to obtain accurate estimates of the spatial spillover effects of urban air pollution.

We obtain gasoline prices from the NDRC website for the sample period.[11] Table 1 reports summary statistics of key variables. With the daily specification for our observations, we have a total number of 146,791 observations. Average API varied substantially in the sample, ranging from 0 to 500, with an average of 68.2. Other control variables, including gasoline price and weather variables, also exhibit significant variability during the sample period. Moreover, the Augmented Dickey-Fuller (ADF), the Elliott-Rothenberg-Stock DF-GLS, and the Phillips-Perron (PP) test statistics indicate that API, weather variables, and gasoline prices are stationary. For brevity, these test statistics are not reported here.

[11] http://www.sdpc.gov.cn/zcfb/zcfbgg/index_2.html

5. Results

5.1 Baseline Results

We conduct the spatial analysis of urban air pollution using four different model specifications. Specifically, in model (1), we include local factors only, namely temporally lagged dependent variable ($API_{i,ysd-1}$), weather variables, and gasoline price as explanatory variables to examine the variations in city-average API during the sample period. In models (2)-(4), we add spatially weighted API as an additional explanatory variable to examine whether a city's air quality is affected by ambient air pollution concentrations in its neighboring cities. In model (2), we employ a simple spatial distance matrix that assigns positive weights to city *i's* neighboring cities based solely on the physical distance between city *i* and its neighboring cities. In model (3), the spatial weights matrix considers not only the physical distance between city *i* and its neighboring cities, but also wind direction and wind speed in city *i's* neighboring cities. In model (4), we incorporate a one-day lag in the spatially lagged API, $\sum_{j\neq i}^{J} \omega_{ij,ysd-1}\, API_{j,ysd-1}$, to account for possible "late arrival" of air pollutants from neighboring cities. Here, the spatial weight matrix $\omega_{ij,ysd-1}$ is slightly different from $\omega_{ij,ysd}$ in that we assign positive weights to city *j* only if it needs 24 hours to 48 hours to transport air pollutants from city *j* to city *i*. Across all model specifications considered here, we include weekend and holiday dummies and city-year-season FE.

The validity of our instruments is supported by both the Hansen test statistics and the Arellano-Bond test statistics for autocorrelation. The Hansen test statistics indicate that our models are not over-identified, while the AR test statistics suggest that lagged variables can be used as instrumental variables. The baseline results are summarized in Table 2.

5.2 Temporal Dependence of Air Pollution

We find that coefficient estimates of the temporally lagged dependent variable ($API_{i,ysd-1}$) are positive and statistically significant at the 1% level in the four model specifications considered here. That indicates the existence of temporal dependence of air pollution. Estimated coefficients of $API_{i,ysd-1}$ range between 0.37 in model (2) to 0.55 in model (3). This suggests, if the average API in a city on a given day increases by one unit, then the average API for the same city on the following day is expected to increase by 0.37-0.55, holding all else the same[12]. The remaining portion (0.45-0.63) of the increase in air pollutants is diluted by nature.

5.3 Spatial Spillover Effects of Air Pollution

In model (2), the coefficient estimate of the spatially lagged API is statistically significant at the 1% level and has a positive sign, which provides strong evidence for the existence of spatial spillover effects of urban air pollution. With the linear specification of the model, the coefficient estimate of this variable can be interpreted as follows: for each unit increase in API in a city's surrounding cities, average air pollution levels in that city are expected to increase by 0.51, holding all else the same. The coefficient estimate of the spatially lagged API is found to be 37% larger than the coefficient estimate of the temporally lagged API, which indicates that neighboring factors might be more important than local factors in contributing to ambient air pollution concentrations. When constructing the spatial weights matrix, model (2) considers only geographic distance between cities and ignores wind direction and wind speed in neighboring cities. That may lead to biased coefficient estimates of various explanatory variables.

In contrast, in addition to geographical distance, the spatial weights matrix in model (3) also considers wind direction and wind speed in surrounding cities. The coefficient estimate of the spatially lagged API is still statistically significant at the 1% level in model (3) but becomes considerably smaller in magnitude (0.41) as compared to the corresponding coefficient estimate in model (2). The coefficient estimate of the spatially lagged API now is 26% smaller than the coefficient estimate of the temporally lagged API. This finding suggests that, in order to obtain accurate coefficient estimates of various explanatory variables, wind direction and wind speed in neighboring cities should be considered when constructing the spatial weights matrix.

In model (4), we add a one-day lag in spatially lagged API as an additional explanatory variable. We find that, although the coefficient estimate of this variable has a positive sign, it is not statistically significant and is quite small. That is probably because, when air pollutants travel a long distance and when wind speed is low, most of the air pollutants can be diluted by natural ecosystems (Kalthoff et al. 2000). Magnitudes, signs, and statistical significance of other

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[12] As a robustness check, we consider two-day lags in API as an additional explanatory variable. We find that, although the coefficient estimate of this variable is statistically significant, the magnitude of this variable is very small and close to zero. Coefficient estimates of other covariates differ only slightly relative to the baseline estimates.

variables are close to our coefficient estimates in model (3), with an exception for the coefficient estimate of the temporally lagged API, which becomes smaller as compared to the corresponding coefficient estimate in model (3).

5.4 Effects of Weather on Air Pollution

The coefficients of precipitation and wind speed variables are negative and statistically significant at the 1% level, although their magnitudes vary slightly across different model specifications. This suggests that increased precipitation and strong winds can effectively reduce air pollution and improve air quality. These findings are in agreement with the well-established literature on atmospheric pollution (see Arya 1998).

Temperature effects on air quality differ over time during a day. The parameter estimate of T_{min} is found to be negative, suggesting that higher T_{min} can reduce city-average API. The mechanism behind this finding is simple. Studies on atmospheric pollution found that when temperature increases, warmer air near the surface becomes lighter than colder air above it, creating an uplift of air. The vertical movement of air can bring certain types of air pollutants away from the surface and thus reduce ground-level air pollution concentrations (Arya 1998).

The coefficient estimate of T_{max} is positive and statistically significant at the 1% level. There are two possible explanations for this finding. First, while T_{min} typically occurs before sunrise, T_{max} usually occurs during the early to middle afternoon. Human activities, such as construction activity and driving for recreation, are also expected to be active during the early to middle afternoon, which may generate traffic exhaust pollutants or other types of air pollutants that cannot be captured by our explanatory variables. Second, high day temperature can stimulate the formation of ozone, which is a major air pollutant. Sillman (1999) found that areas with warmer climate tend to experience higher levels of ozone. Similar to Viard and Fu (forthcoming), we also find that ambient air pollution levels are negatively correlated with solar radiation.

5.5 Effects of Other Factors

Parameter estimates of other control variables are also consistent with the literature. The coefficient estimate of gasoline price is negative and statistically significant at the 1% level in all model specifications. It indicates that raising fuel price is an effective economic instrument to curb urban air pollution, possibly by reducing fuel consumption and vehicle miles travelled. Coefficient estimates of the weekend and holiday variables are statistically significant and have positive and negative signs, respectively. These are expected results given that urban residents typically spend their weekends in cities, which may lead to increased pollution stemming from traffic exhaust, cooking, and other factors. On the other hand, many Chinese residents living in urban areas take some time off and travel to their rural home during national holidays, which may result in traffic congestion on highways but may reduce air pollution levels in urban areas.

5.6 Robustness Checks

The results presented above regarding the impacts of various factors on urban air pollution make intuitive sense. But how robust are they? In this section, we examine the sensitivity of our results in nine different scenarios.

To test the sensitivity of our results to location, we divide the sample into two regions in Scenarios (1)-(2): western cities and eastern cities, based on the guidelines provided by the National Bureau of Statistics of China (NBS). In Scenarios (3)-(4), we separate the sample into northern cities and southern cities according to the Huai River-Qin Mountains line, which is the natural boundary between northern China and southern China.

We also assess the robustness of our results using different spatial weights matrices in Scenarios (5)-(6). In Scenario (5), we reduce the distance radius from 500 kilometers to 300 kilometers and examine whether this change will affect our coefficient estimates. Although the cities included in the sample are large, they differ by population, economic scale, and air pollution concentrations. To capture the effects of city size on estimated spatial spillover effects of air pollution, in Scenario (6) the spatial weights matrix considers city-specific GDP in addition to physical distance, wind direction, and wind speed. If a city's surrounding city has a higher level of GDP, then the weight assigned to this surrounding city is also larger, holding other factors the same.

Lastly, we test the sensitivity of our results to variations in variables and econometric estimation strategies in Scenarios (7)-(9). More specifically, in Scenario (7), we use city-year-month FE rather than city-year-season FE to control for a wider range of time-varying unobserved factors. In Scenario (8), we use daily T_{ave} rather than T_{min} and T_{max} as a temperature variable. In Scenario (9), we treat gasoline price and weather variables as exogenous variables and replicate the above analysis. We conduct these robustness checks using model specification (3), and change one assumption at a time.

Table 3 shows the regression results when the sample is divided into different regions. There are two major differences in comparison to the baseline results. First, the magnitude of the coefficient estimate of the spatially lagged API variable in Scenario (2) becomes substantially smaller (0.198 vs. 0.405), although it has the expected sign and statistical significance. That is possibly because cities located in western China are less developed relative to cities in other regions and the number of cities located in this part of the country is relatively small. As a result, the spatial spillover effects of air pollution in this region are smaller as compared to those in other regions. Second, the coefficient estimate of gasoline price in Scenario (2) still has a negative sign but becomes statistically insignificant. Signs and statistical significance of coefficient estimates of weather variables are consistent with our baseline estimates.

Table 4 shows that our regression results remain robust to variations in spatial weights matrices in Scenarios (5)-(6) and the city-year-month FE in Scenario (7). In the three scenarios, estimated coefficients of the spatially lagged API and the temporally lagged API variables and weather variables are consistent with our baseline estimates. In Scenario (8), we use T_{ave} as the temperature variable. The coefficient estimate of T_{ave} is positive and statistically significant at the 1% level, suggesting that elevated T_{ave} may have caused higher levels of ozone and other economic activities, such as more construction activity and more driving, that generate air pollutants. Coefficient estimates of other explanatory variables in Scenario (8) are close to the baseline estimates, with an exception for coefficient estimate of the solar radiation variable, which becomes statistically insignificant. When gasoline price and weather variables are treated as exogenous variables in Scenario (9), we find that signs, magnitudes, and statistical significance of explanatory variables are comparable with our baseline estimates.

6. Conclusion and Discussion

With the rapidly deteriorating air quality in China, identifying key air pollution sources is the critical first step before efficient strategies can be developed to solve this problem. In this paper, we compile a unique city-level panel that contains rich information on urban air pollution, weather conditions, and fuel prices to evaluate the effects of various factors affecting urban air quality in China.

To fully incorporate the spatial and temporal dynamics of air pollution, we develop a dynamic spatial panel model. The spatial weights matrix constructed in the model considers not only geographical distance, but also wind direction and wind speed in neighboring cities. The spatial econometric model we developed in this paper is novel, as it is the first empirical study that allows a spatial weights matrix to change daily.

Our regression results provide strong evidence of the existence of spatial spillover effects of air pollution. The importance of neighboring factors will be significantly overestimated with a traditional distance weights matrix, under which the coefficient estimate of the spatially lagged API is about 0.51. But it drops to 0.40-0.41 when the spatial weights matrix is properly specified. As compared to the spatial correlations of air pollution, the temporal dependence of air pollution is significantly larger across different model specifications (0.45-0.61 versus 0.20-0.46). Coefficient estimates of other variables, including weather variables and gasoline price, have expected signs and statistical significance, which are consistent with findings presented in the atmospheric pollution literature. These results remain robust to locations, alternative spatial weights matrices, different sets of control variables, and econometric estimation strategies.

Given the existence of transboundary air pollution from upwind cities, the widely-adopted strategy of relocating large-scale and heavily polluting factories to suburbs or to neighboring cities in China will not be effective. To effectively abate transboundary air and water pollution, pollution control policies must be coordinated between cities and provinces. Our findings also show that China should adopt the U.S. EPA's Good Neighbor Rule that is designed to address interstate transport of air pollution.

Two major caveats apply. First, our sample includes 119 major Chinese cities and we investigate the spatial correlations of air pollution among these major cities. However, there are many small and medium cities located between these major cities, and air pollutants in these small and medium cities may be transported to major cities by wind. As a result, our estimated spatial spillover effects of air pollution could be smaller or larger than the actual effects. Second, when constructing the spatial weights matrix, we do not consider whether there exist large mountains between a pair of cities. Large mountains can effectively prevent the transport of air pollutants. Nonetheless, we have used a unique dataset and provided empirical evidence of the existence of spatial spillover effects of air pollution in China.

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Table 1. Descriptive Statistics

Variable		Mean	SD	Min	Max
API		68.2	30.7	0.0	500.0
Gasoline price	Yuan/ton	8595.3	947.9	6115.0	10380.0
Precipitation	0.1 mm	28.8	103.3	0.0	3498.0
Solar radiation	0.1 hour	56.8	42.3	0.0	147.0
T_{max}	0.1°C	194.1	112.5	-257.0	435.0
T_{min}	0.1°C	104.5	115.5	-352.0	326.0
Average wind speed	0.1 m/s	22.7	13.9	0.0	203.0

Notes: The sample contains 119 major cities in China from 2009 to 2013. *N*=146,791.

Table 2. Baseline results (dependent variable: API)[1]

Variables	Model (1): Local factors only	Model (2): Distance weighted	Model (3): Distance, wind direction, wind speed weighted	Model (4): Distance, wind direction, wind speed weighted
Temporally lagged API	0.496***	0.371***	0.549***	0.456***
	(0.013)	(0.015)	(0.015)	(0.014)
Spatially lagged API		0.509***	0.405***	0.403***
		(0.033)	(0.022)	(0.022)
Spatially lagged API_{d-1}				0.014
				(0.019)
Gasoline price	-0.001***	-0.005***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.085***	-0.050***	-0.065***	-0.070***
	(0.006)	(0.005)	(0.006)	(0.006)
Solar radiation	-0.280***	-0.163***	-0.195***	-0.211***
	(0.015)	(0.013)	(0.013)	(0.014)
T_{max}	0.314***	0.198***	0.243***	0.246***
	(0.012)	(0.012)	(0.012)	(0.012)
T_{min}	-0.306***	-0.185***	-0.235***	-0.241***
	(0.012)	(0.012)	(0.012)	(0.012)
Average wind speed	-0.339***	-0.192***	-0.611***	-0.592***
	(0.030)	(0.026)	(0.034)	(0.036)
Holiday	-2.134***	-1.192***	-1.783***	-1.748***
	(0.362)	(0.339)	(0.403)	(0.413)
Weekend	1.181***	0.960***	1.005***	1.070***
	(0.207)	(0.182)	(0.213)	(0.211)
Hansen test[2]	0.685	1.000	0.718	1.000
AR(1)[2]	0.000	0.000	0.000	0.000
AR(2)[2]	0.072	0.086	0.677	0.191
Observations	146,791	146,791	146,791	146,791

Notes: [1]City-year-season dummies are included in all model specifications. Asymptotic standard errors, asymptotically robust to heteroskedasticity, are reported in parentheses. N=146,791.

[2]These numbers are p values of the over-identification and serial correlation tests.

*** p<0.01, ** p<0.05, * p<0.1

Table 3. Sensitivity Analysis by Region (Dependent Variable: API)[1]

	Scenario (1): Eastern cities	Scenario (2): Western cities	Scenario (3): Southern cities	Scenario (4): Northern cities
Temporally lagged API	0.543***	0.605***	0.546***	0.524***
	(0.018)	(0.025)	(0.020)	(0.018)
Spatially lagged API	0.368***	0.198***	0.370***	0.318***
	(0.023)	(0.030)	(0.033)	(0.020)
Gasoline price	-0.002***	-0.000	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.057***	-0.054***	-0.034***	-0.084***
	(0.006)	(0.007)	(0.004)	(0.007)
Solar radiation	-0.153***	-0.200***	-0.081***	-0.219***
	(0.012)	(0.021)	(0.011)	(0.014)
T_{max}	0.205***	0.261***	0.200***	0.212***
	(0.012)	(0.019)	(0.012)	(0.012)
T_{min}	-0.199***	-0.269***	-0.202***	-0.209***
	(0.012)	(0.020)	(0.013)	(0.012)
Average wind speed	-0.617***	-0.167***	-0.548***	-0.372***
	(0.034)	(0.055)	(0.031)	(0.042)
Hansen test[2]	1.000	1.000	1.000	1.000
AR(1)[2]	0.000	0.000	0.000	0.000
AR(2)[2]	0.380	0.915	0.048	0.769
Observations	102,846	43,945	72,748	74,043

Notes: [1]In Scenarios (1)-(2), we divide the sample into eastern cities and western cities, while in Scenarios (3)-(4) the sample is separated into southern cities and northern cities. City-year-season dummies are included in all model specifications. Asymptotic standard errors, asymptotically robust to heteroskedasticity, are reported in parentheses. Holiday and weekend variables have expected signs and statistical significance. For brevity, they are not reported here.

[2]These numbers are *p* values of the over-identification and serial correlation tests.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4. Sensitivity Analysis by Estimation Strategy (Dependent Variable: API)[1]

	Alternative spatial weights matrix		Alternative model specifications		
	Scenario (5): distance cutoff at 300km	Scenario (6): considering GDP	Scenario (7): city-year-month FE	Scenario (8): T_{ave} as temperature variable	Scenario (9): exogenous gasoline price and weather variables
Temporally lagged API	0.554*** (0.015)	0.548*** (0.015)	0.484*** (0.018)	0.594*** (0.015)	0.447*** (0.014)
Spatially-lagged API	0.415*** (0.024)	0.405*** (0.022)	0.440*** (0.029)	0.462*** (0.022)	0.424*** (0.025)
Gasoline price	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)
Precipitation	-0.067*** (0.006)	-0.065*** (0.006)	-0.097*** (0.008)	-0.069*** (0.006)	-0.066*** (0.006)
Solar radiation	-0.216*** (0.013)	-0.195*** (0.013)	-0.291*** (0.025)	0.001 (0.008)	-0.201*** (0.016)
T_{max}	0.262*** (0.012)	0.243*** (0.012)	0.331*** (0.022)		0.244*** (0.014)
T_{min}	-0.254*** (0.012)	-0.236*** (0.012)	-0.294*** (0.021)		-0.225*** (0.014)
T_{ave}				0.006** (0.003)	
Average wind speed	-0.558*** (0.033)	-0.611*** (0.034)	-0.598*** (0.042)	-0.807*** (0.036)	-0.594*** (0.039)
Hansen test[2]	0.881	0.717	0.000	0.024	0.311
AR(1) [2]	0.000	0.000	0.000	0.000	0.000
AR(2) [2]	0.706	0.644	0.664	0.360	0.144
Observations[3]	144,028	146,791	146,791	146,791	146,791

Notes: [1]In Scenario (5), when constructing the spatial weights matrix, we reduce the distance cutoff from 500 kilometers to 300 kilometers. In Scenario (6), we consider sizes of different cities when constructing the spatial weights matrix. In Scenario (7), we use city-year-month FE. In Scenario (8), T_{ave} is used as a temperature variable. In Scenario (9), gasoline price and weather variables are treated as exogenous variables. City-year-season dummies are included in all specifications. Asymptotic standard errors, asymptotically robust to heteroskedasticity, are reported in parentheses. Holiday and weekend variables have expected signs and statistical significance. For brevity, they are not reported here.

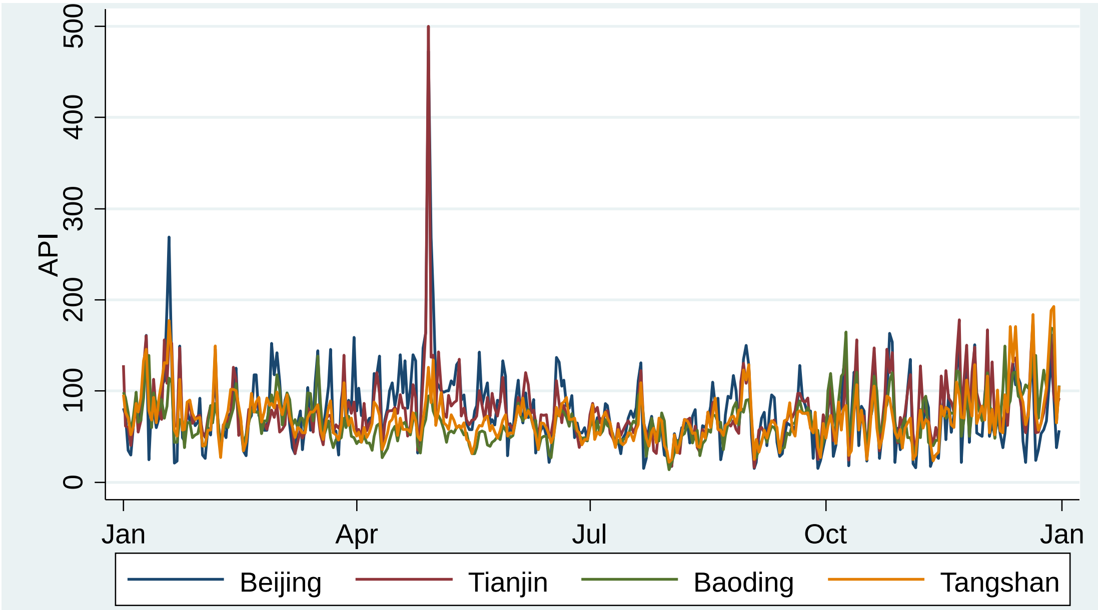
[2]These numbers are p values of the over-identification and serial correlation tests.

[3]In Scenario (5), we lose two cities located in northwestern China because the distance between the two cities is greater than 300 kilometers. As a result, the number of observations in this scenario is reduced to 144,028.

*** p<0.01, ** p<0.05, * p<0.1

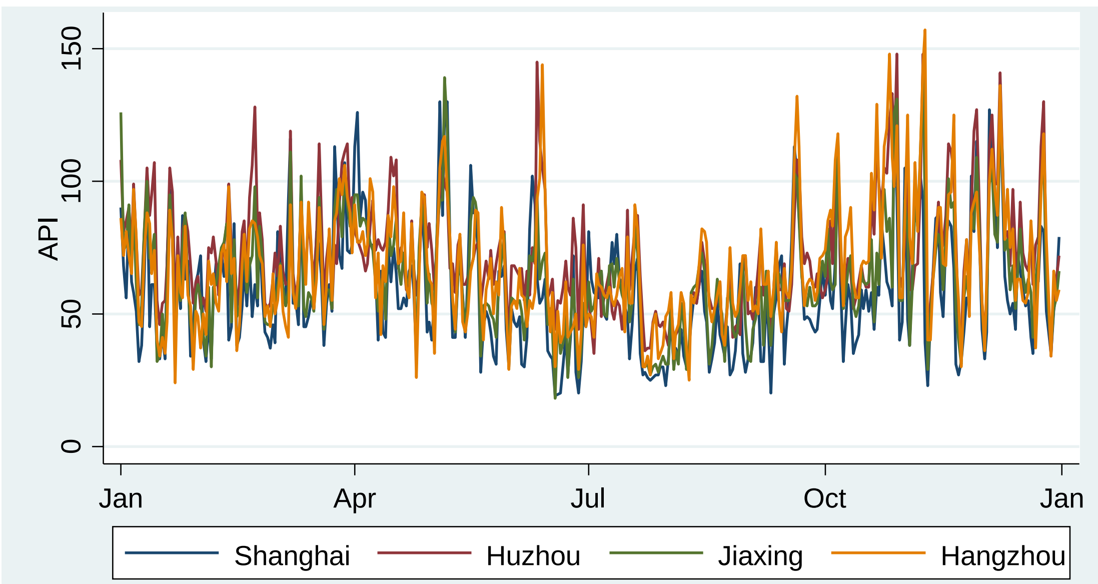
Figure 1. Spatial Distribution of the Cities Included in the Sample

Figure 2. Spatial Correlations of Air Pollution in Chinese Cities



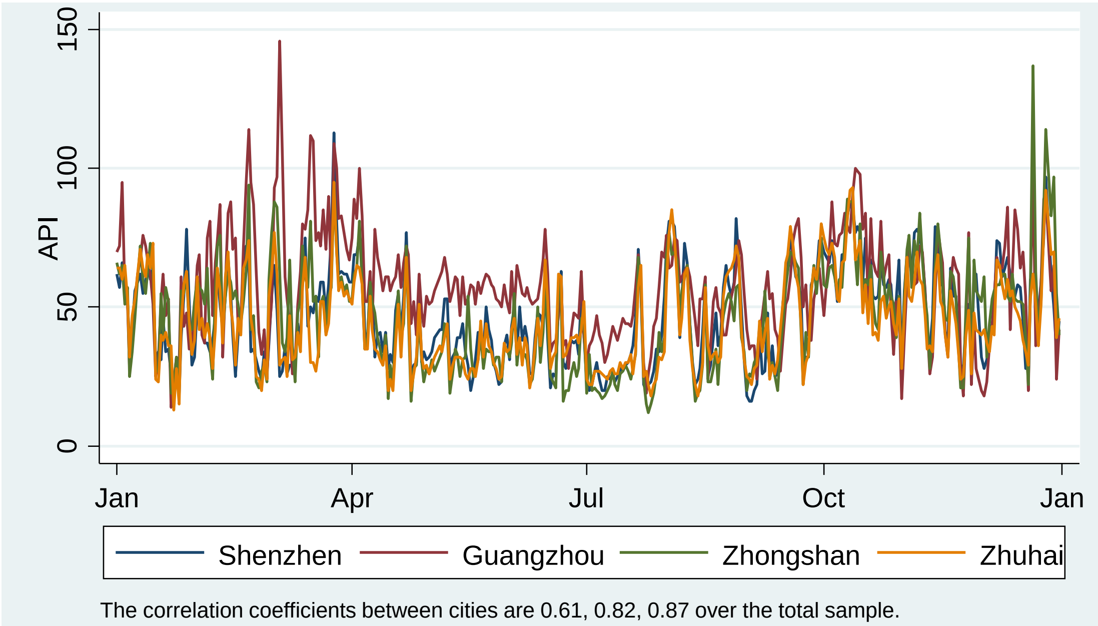
The correlation coefficients between cities are 0.69, 0.39, 0.55 over the total sample.

(a) Beijing and its neighboring cities

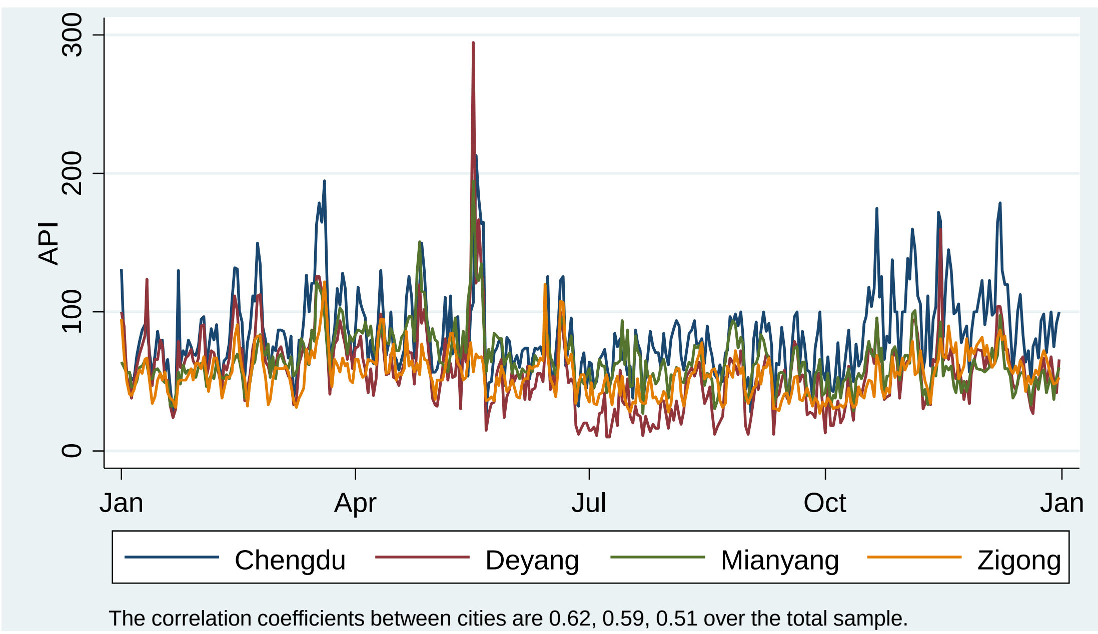


The correlation coefficients between cities are 0.65, 0.82, 0.68 over the total sample.

(b) Shanghai and its neighboring cities



(c) Shenzhen and its neighboring cities



(d) Chengdu and its neighboring cities

Note: Figure 2 is based on the 2012 API data for four major cities that are located in different areas in China.

Figure 3. Wind Rose Plots for Beijing, Shanghai, Shenzhen, and Chengdu in 2012