**When the Wind Blows: Spatial Spillover Effects of Urban Air Pollution**

Xiaoguang Chen
Research Institute of Economics and Management, Southwestern University of Finance and Economics, No. 55 Guanghuacun Street, Chengdu, China 610074
Email: cxg@swufe.edu.cn

Jingjing Ye
Research Institute of Economics and Management, Southwestern University of Finance and Economics, No. 55 Guanghuacun Street, Chengdu, China 610074
Email: jingjingye@swufe.edu.cn

***Selected Paper prepared for presentation at the 2017 Agricultural & Applied Economics Association Annual Meeting, Chicago, Illinois, July 30-August 1***

**When the Wind Blows: Spatial Spillover Effects of Urban Air Pollution**


## ABSTRACT

This paper investigates the existence and magnitude of air pollution spillovers in Chinese cities. Estimation of this spillover effect is complicated because neighboring cities share similar business/pollution cycles and meteorological conditions and because spatial and temporal changes in wind direction can be fairly frequent. To circumvent these empirical challenges, we exploit spatial and temporal variations in $PM_{10}$ concentrations for the 108 major cities located in China's Eastern Monsoon Region during the East Asian winter and summer monsoon seasons. We have three main findings. First, we find large pollution spillover effects in Chinese cities: a city's average $PM_{10}$ concentration is expected to increase by 0.09-0.21 units during the winter monsoon season and by 0.06-0.10 units during the summer monsoon season, if the average $PM_{10}$ concentrations in cities upwind of this city increase by one unit. Second, high levels of precipitation and strong winds can effectively mitigate air pollution, while the temperature effects on air quality vary by time of day. Third, the percentage contributions of $PM_{10}$ pollution from upwind cities to local $PM_{10}$ levels vary by region and can be as large as 30%. Our findings suggest that pollution control policies must be coordinated between cities and provinces to effectively abate urban air pollution.



*Keywords*: Pollution spillovers; $PM_{10}$; Wind; Monsoon; China

*JEL classification*: Q53, C23

## 1. Introduction

China's poor air quality has put the country in the world's spotlight. In many Chinese cities, pollution levels exceeded the World Health Organization air quality guidelines on more than 250 days in 2011 (Cheng et al., 2013). International media has described air quality in China as "hazardous to human health".[1] Negative health consequences have been repeatedly reported, including premature death (Yang et al., 2013; Zhang et al., 2010) and significant reduction in average life expectancy (Chen et al., 2013a). Air pollution is also linked to China's growing social unrest in recent years.[2]

This paper aims at identifying the contributions of various pollution sources to ambient air pollution concentrations in Chinese cities. As the economics literature is relatively new to this topic, we first give a brief overview of previous approaches used by atmospheric scientists to set the stage for our study. These approaches can be divided into two major categories, including the air sampling approach and Air Quality (AQ) models. The air sampling approach entails measuring the content of particulate and gaseous contaminants in collected air samples. By analyzing ambient gases and aerosol properties in air samples,[3] atmospheric scientists can pin down the contributions of various sources, such as primary emissions vs. secondary formation and local sources vs. regional transport, to ambient pollution concentrations (Guo et al., 2014). However, results based on this approach are quite sensitive to sampling sites, duration of sampling periods and sampling methods (Katz, 1969).[4]

---

1 "China smog sparks red alerts in 10 cities," *BBC news*, December 24, 2015.
2 "Chinese anger over pollution becomes main cause of social unrest," *Bloomberg*, March 6, 2013.
3 Common measurements include pollutant concentrations, size distribution, chemical composition, and temporal evolution of air pollutants.
4 For instance, using the data collected at Peking University located in northwestern Beijing (an urban site) 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 from the same site during a different time period, from September to November 2013, Guo et al. (2014) concluded that nitrogen oxides ($NO_x$) from local transportation and sulfur dioxide ($SO_2$) from regional industrial sources were the main sources of air pollution in Beijing.

The AQ models are another widely-used approach to assess the contributions of various factors to ambient air pollution concentrations. Instead of analyzing collected air samples, the AQ models utilize complex mathematical techniques to simulate transport and diffusion processes of air pollutants in the atmosphere. An example is Models-3/Community Multi-scale Air Quality (CMAQ), developed by the US Environmental Protection Agency (EPA). Using CMAQ and a modified version of the model (MM5–CMAQ), respectively, Streets et al. (2007) and Chen et al. (2007) concluded that neighboring provinces, such as Hebei, Shandong, and Tianjin, had a large influence on Beijing's air quality. Although the AQ models can identify pollution sources by building source-destination relationships, several studies have pointed out that simulation results based on the AQ models are sensitive to grid resolutions (Queen et al., 2008; Queen and Zhang, 2008), and the computational costs of running these AQ models can be quite substantial (see Capaldo et al., 2000).

In this paper, we employ an econometric approach. We develop a spatial dynamic panel data (SDPD) model to quantify the effects of various local and neighboring factors on air quality in Chinese cities. We also use this framework to assess the percentage contributions of air pollution spillovers from upwind cities to local air pollution. As compared to the atmospheric approaches mentioned above, the SDPD model developed here has at least three advantages. First, by explicitly including an extensive list of explanatory variables, our approach leads to a clearer understanding of the impacts of various local and neighboring factors on urban air quality. Our SDPD model includes not only meteorological factors (as in most atmospheric studies), but also considers the effects on local air quality of agricultural activities, energy consumption, holidays/weekends, and air pollution from upwind cities. Second, our approach allows us to fully utilize high-frequency data consisting of daily meteorological conditions and air pollution, while most of the AQ models use only seasonal/monthly data to minimize computational costs (Capaldo et al., 2000). Third, as compared to the atmospheric approaches, our approach yields more robust results that are not sensitive to study periods, study sites, and estimation techniques, which are explained in detail in the results section.

However, estimation of this pollution spillover effect is complicated for two reasons. One, the observed pollution in a city is an outcome of local activities and possible spillovers from upwind cities and neighboring cities usually share similar business/pollution cycles and meteorological conditions, which make separating pollution spillovers from locally generated pollution difficult. Two, we observe frequent spatial and temporal changes in wind direction in our data, making it even more difficult than in other contexts[5] to identify pollution spillovers. For example, wind can carry air pollutants from one city to its downwind areas on one day. These pollutants, together with pollutants generated from the downwind areas, could be transported back to the original city on the following day, due to changes in wind direction.

To circumvent the empirical challenges noted above, we restrict our focus to observations of the 108 major cities located in the Eastern Monsoon Region (EMR) in China[6] during the East Asian winter monsoon (EAWM) and the East Asian summer monsoon (EASM) seasons. The most notable feature of the EAWM is strong and stable northwesterly winds across the east flank of the Siberian high and the East Asia coast including China's EMR (Zhou, 2011), while the prevailing winds have been southerly and southwesterly during the EASM season (Ding, 1994). By restricting our sample to

[5] Such as transboundary water pollution spillovers (Sigman, 2002).

[6] According to climatological and topographical characteristics, China can be divided into three main regions, including the Eastern Monsoon Region, the Qinghai-Tibetan Plateau Region and the Northwestern Arid Region (Figure 1).

these major cities in the EMR during the two monsoon seasons, we can obtain clean estimates of pollution spillover effects. This identification strategy is similar to that used by Jia and Ku (2016). They assess the impacts of cross-border air pollution from China to South Korea by exploiting the meteorological phenomenon known as Asian dust, in which yellow dust clouds, together with air pollution in China, are transported eastward to South Korea by strong westerly winds.

We conduct this analysis by compiling a unique city-level panel that contains daily air quality and weather information for the 108 major cities located in the EMR from 2009 to 2013 (see Figure 1). We use the concentration of particulate matter with a diameter of 10 μm or less ($PM_{10}$) as our dependent variable. We focus on $PM_{10}$ for two reasons. First, $PM_{10}$ is the primary air pollutant in Chinese cities (Chan and Yao, 2008). Second, $PM_{10}$ can travel long distances (Duce et al., 1980; Parrington et al., 1983; Tsunogai and Kondo, 1982), while other major air pollutants, such as $SO_2$, $NO_x$, ozone, and carbon monoxide, are either exclusively from local emissions sources or can only be transported within relatively small geographic regions (Guo et al., 2014). Therefore, focusing on $PM_{10}$ can better serve our research purpose, which is to examine the existence and magnitude of spatial spillover effects of urban air pollution.

Our regression model includes a wide range of local and neighboring factors as explanatory variables. Local factors include a temporally lagged dependent variable, which represents a city's air pollution stock; weather conditions, such as temperature, precipitation, solar radiation, wind speed, relative humidity and atmospheric pressure; the gasoline price, which is used to control for $PM_{10}$ released from vehicle exhaust; and open-field burning of crop residues during post-harvest seasons. We account for the effect of $PM_{10}$ from upwind cities on local $PM_{10}$ concentrations by creating a spatially-weighted $PM_{10}$ variable that depends on physical distance between cities, wind direction, wind speed and emission strength in upwind cities. Finally, we augment the model by using city-year-month fixed effects to minimize the potential estimation biases originating from omitted variables. The high dimensional fixed effects capture a wide range of the unobserved factors within a city-year-month that may affect city-average $PM_{10}$ concentrations. These unobserved factors may include economic shocks, seasonal coal combustion for heat and power generation, dust generated from occasional sand storms and/or from the construction of new buildings and roads, number of vehicles, and perhaps others.

We find strong evidence of the existence of spatial spillover effects of $PM_{10}$ pollution in China. Holding all else the same, a one-unit increase in $PM_{10}$ concentrations in upwind cities of a city is expected to raise that city's $PM_{10}$ concentration by 0.09-0.21 unit during the winter monsoon season, and by 0.06-0.13 during the summer monsoon season. Impacts of upwind air pollution on local $PM_{10}$ concentrations vary across regions, with cities located in the North China Plain and Yangtze River Delta regions most affected by air pollution from upwind cities.

Our findings are highly relevant to the design of China's air pollution control strategies. 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 are found to come primarily from upwind 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., 2013b). 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. By using high quality data and a rigorous approach to identify the effects of various local and neighboring factors on urban air quality, our results may stimulate public policy debates regarding how to effectively design China’s air pollution control policies.

In addition to using a new approach to assess the impacts of various factors on air pollution, this paper contributes to the existing literature in four major aspects. First, our spatial econometric model is novel. When conducting spatial econometric analyses, many studies specify spatial weights matrices based on either geographical criteria or economic dependence between regions/sectors. These studies typically assume that spatial weights matrices are time-invariant (see Anselin and Bera, 1997; Won Kim et al., 2003), ignoring the fact that, under certain circumstances, spatial dependence of two regions/sectors may change over time. In contrast to these studies, we allow our spatial weights matrix to change daily according to wind direction and wind speed in upwind cities. Although our approach is different from the atmospheric approaches, our results are fairly comparable to the atmospheric evidence.

Second, our data set is rich and comprehensive. Existing studies examining the spatial spillover effects of air pollution in China have primarily focused on Beijing and the data used in these earlier studies span only a short period of time (see Guo et al., 2014; Zhang et al., 2013). Our city-level panel data set includes major Chinese cities located in the EMR and contains detailed information on daily air quality and weather conditions for these cities during the period 2009-2013. The unique data structure enables us to construct city-year-month fixed effects, which can minimize the potential estimation biases due to omitted variables.

Third, the study provides a new way to construct an instrumental variable for air quality. When examining the impacts of air pollution on housing values, Chay and Greenstone (2005) used nonattainment status as the instrumental variable for air quality.[7] Luechinger (2009) improved Chay and Greenstone's approach and used the changes in $SO_2$ concentration due to the mandated installation of $SO_2$ emissions control equipment in upwind areas as an instrument for $SO_2$ pollution. We demonstrate that air pollution from areas upwind of a city can serve as a valid instrumental variable for that city's air quality. That is because air pollution levels are likely to be spatially correlated, but local economic indicators, such as housing values, unemployment rates and labor income, are unlikely to be correlated with air pollution in other regions.

Lastly, 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 US 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 between adjacent cities/provinces are needed to control for transboundary air pollution.

[7] Under the Clean Air Act, the US EPA designates a county as in "nonattainment" status if pollution concentrations in this county exceed the federally determined ceiling.

The rest of the paper is organized as follows. Section 2 discusses related background on regional transport of particulate matter. Section 3 illustrates various factors that may affect urban $PM_{10}$ concentrations in China. Section 4 presents our empirical model and identification strategy. Section 5 describes data sources and summary statistics. Section 6 presents baseline results. Section 7 considers a variety of robustness checks. Section 8 assesses the percentage contributions of $PM_{10}$ pollution from upwind cities. Section 9 concludes.

## 2. Regional transport of particulate matter

Particulate matter (PM) is a mixture of small particles and liquid droplets floating in the air. The composition of PM varies with location, time, and weather conditions (Allen et al., 1997). It mainly includes aerosols, smoke, fumes, dust and ash, originating from both human and nature activities. PM can be created directly from fossil fuel combustion, road or windblown dust, and combustion of agricultural and forest biomass, or can be formed in the atmosphere through multiphase chemical reactions. Natural sources, such as volcanoes, dust storms, and wildfires, also contribute to the overall PM formation.

PM can be divided into two types according to size: $PM_{10}$ (or coarse particles) and $PM_{2.5}$ (or fine particles) with a diameter of 2.5 μm or less. $PM_{10}$ and $PM_{2.5}$ behave differently in the atmosphere. In general, $PM_{10}$ may spread out more rapidly than $PM_{2.5}$ and usually can be found close to the emission sources, while $PM_{2.5}$ can be transported long distances by wind. However, the long-distance transport of major particle components of $PM_{10}$, such as yellow sand and aerosols, has also been observed. For instance, Duce et al. (1980) and Parrington et al. (1983) found that Asian dust was transported to the tropical North Pacific and Hawaiian islands, respectively. Recent studies have also discovered that yellow sand originating from dust storms in Mongolia, the Gobi desert, and the Loess Plateau can be transported by wind to Taiwan and Korea (Jia and Ku, 2016; Kim and Park, 2001; Lin, 2001).

Transporting PM in the atmosphere from emission sources to destinations is a very complex process (Arya, 1999). The transport processes of PM in the atmosphere can be divided into two independent processes: (*i*) advection of PM in the direction of wind by mean air motion; and (*ii*) mass diffusion due to concentration gradients. Diffusion occurs in both the horizontal crosswind direction and the vertical crosswind direction (Ermak, 1977). Ermak (1977) developed an analytical model for air pollutant transport from a point source, assuming flat terrain, constant average wind velocity, and unlimited atmosphere in the vertical direction. He showed that the steady-state downwind pollutant concentration is positively correlated with emission strength, and negatively correlated with distance and average wind speed at the point source (see Eq. (5) in Ermak, 1977). These analytical findings are consistent with other well-known atmospheric dispersion models, such as the Gaussian plume model (Foster-Wittig et al., 2015) and the CALINE3 model, which is one of the US EPA's preferred air pollutant dispersion models (Mishra and Padmanabhamutry, 2003). Building on the conceptual insights presented in Ermak (1977), we construct our spatial weights matrices, which are discussed in detail in Section 4.

## 3. Contributing factors to $PM_{10}$ pollution in Chinese cities

Based on their origins, we categorize the factors affecting a city's $PM_{10}$ concentration into local and neighboring factors. Local factors include weather, combustion of fossil fuels, economic activities, and city-specific environmental protection measures. Neighboring factors refer to $PM_{10}$ transported from upwind regions by the passage of wind. In this section, we discuss each of these factors.

*3.1 Local factors*

Weather conditions, such as precipitation, wind, temperature, sunshine, relative humidity, and atmospheric pressure, have been well recognized as important factors affecting ambient $PM_{10}$ concentrations. Precipitation can increase the weight of PM that is floating in the air and cause the particles to fall. Strong winds can facilitate atmospheric dispersion and thus reduce $PM_{10}$ concentrations. While wind affects the horizontal movement of $PM_{10}$, the literature on atmospheric pollution suggests that temperature influences the vertical movement of $PM_{10}$ (Arya, 1999). 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 $PM_{10}$ away from the ground level, and reduce ground-level $PM_{10}$ concentrations. Other weather variables, such as sunshine hours, relative humidity, and atmospheric pressure, are also important factors affecting local $PM_{10}$ concentrations (Arya, 1999; Pankow et al., 1993).

The primary source of $PM_{10}$ pollution in Chinese cities is combustion of fossil fuels, including vehicle fuel consumption and coal burning for winter heating and industrial production. China's private car sector has experienced explosive growth during the past decade. The number of privately owned vehicles in Chinese cities increased from 7.7 million in 2001 to 88.4 million in 2012, with an average annual rate of growth of nearly 25% (NBS, 2012). A recent emission inventory indicates that, although contributions of vehicles to urban air pollution differ by region, vehicle emissions are a major contributor to the overall PM problem in many Chinese cities.[8] As the primary energy source in China, burning coal in industrial sectors, such as cement, paper, and chemical factories, is also associated with the release of PM.

Rapid urbanization is another important local factor contributing to the formation of $PM_{10}$. Massive infrastructure construction in China in the past decade has generated a significant amount of dust.[9] Finally, as noted above, the burning of crop residues and occasional sand storms have also contributed to poor air quality.

On the mitigation side, central and local governments have undertaken various efforts to improve air quality, including closing heavily polluting facilities, regulating the content of gasoline and diesel, saving energy during construction, and requiring coal-powered plants to install and operate dust-removing technologies (Zhao and Gallagher, 2007). Driving restrictions have also been implemented by some Chinese cities to reduce traffic congestion and improve air quality, although the impacts of those policies are found to be mixed (Viard and Fu, 2015; Wang et al., 2014).

*3.2 Neighboring factors*

Because wind can transport certain air pollutants from one region to other regions, ambient $PM_{10}$ concentrations in areas downwind of a city are expected to be negatively affected by $PM_{10}$ released in that city. Guo et al. (2014) discovered that pollutants emitted from industrial sectors in Beijing's neighboring provinces contributed substantially to the PM formation in Beijing. Kallos et al. (1998) found evidence that the wind blew polluted air from southern Europe to Africa. The US

[8] "China vehicle emissions control annual report," available at: http://transportpolicy.net/index.php?title=China:_Compliance_and_Enforcement
[9] The Chinese-language version of the website is available at: http://www.bjepb.gov.cn/bjepb/323474/331443/331937/333896/396191/index.html

EPA also believes that international transport of air pollution has a significant negative impact on US air quality.[10]

## 4. Empirical methodology

### *4.1 Model specification*

Following the above discussion, we estimate a regression model that accounts for both spatial and temporal correlations of $PM_{10}$ concentrations and considers a variety of local and neighboring factors that may affect urban $PM_{10}$ concentrations. Formally, we estimate:

$$PM_{i,ymd} = \tau PM_{i,ymd-1} + \rho_1 \sum_{j\neq i}^{J} \omega_{ij,ymd} PM_{j,ymd} + \rho_2 \sum_{j\neq i}^{J} \omega_{ij,ymd-1} PM_{j,ymd-1} + X_{i,ymd}\beta + \mu_{i,ym} + \varepsilon_{i,ymd} \quad (1)$$

where $PM_{i,ymd}$ denotes the daily average $PM_{10}$ concentration for city *i* on day *d* in month *m* of year *y*, while $PM_{j,ymd}$ denotes the daily average $PM_{10}$ concentration for city *i's* upwind city *j* on the same day. $\omega_{ij,ymd}$ ($\omega_{ij,ymd-1}$) is the weight assigned to the upwind city *j* by city *i* on day *d* (*d-1*) in month *m* of year *y*. Thus, $\sum_{j\neq i}^{J} \omega_{ij,ymd} PM_{j,ymd}$ ($\sum_{j\neq i}^{J} \omega_{ij,ymd-1} PM_{j,ymd-1}$) denotes the aggregate amount of $PM_{10}$ transported from cities upwind of city *i* to city *i* on day *d* (*d-1*) in month *m* of year *y*. In the remainder of this paper, we call $\sum_{j\neq i}^{J} \omega_{ij,ymd} PM_{j,ymd}$ "the spatially-lagged $PM_{10}$ variable", and call $\sum_{j\neq i}^{J} \omega_{ij,ymd-1} PM_{j,ymd-1}$ "the spatially and temporally-lagged $PM_{10}$ variable". As noted above, we restrict our sample to observations of cities located in China's EMR during the East Asian monsoon seasons. Thus, $PM_{10}$ concentrations in city *i* may be affected by $PM_{10}$ pollution spilled over from upwind

10 "International transport of air pollution," available at: http://www.millenniumbulkeiswa.gov/comments/MBTL-EIS-0002256-58930.pdf

cities during a given monsoon season, but city $i$'s $PM_{10}$ concentrations are unlikely to influence $PM_{10}$ concentrations in its upwind cities during the same monsoon season.

$X_{i,ymd}$ is a vector of variables describing local conditions in city *i* on day *d* in month *m* of year *y*. $\mu_{i,ym}$ denotes the city-year-month fixed effects that capture a wide range of the unobserved factors that are common to a city in a given year and month, such as seasonal coal consumption (in particular in North China, where coal is used for winter home and office heating), construction of buildings, subways and new roads, occasional sand storms, and policies implemented by different levels of government to improve air quality. The high dimensional fixed effects can also account for the effects of regional economic shocks and/or changes in regional meteorological conditions in a given year and month on $PM_{10}$ pollution. $\varepsilon_{i,ymd}$ are the idiosyncratic error terms.

The atmospheric pollution literature suggests that there exists some degree of natural dilution of air pollution (Mayer, 1999). We make two assumptions to simplify our regression model (1). First, we assume that the temporal dependency of $PM_{10}$ concentrations in a city exists only between day *d* and day *d-1*. $\tau$ captures this temporal dependency. Second, a city's $PM_{10}$ concentration on a given day is assumed to be affected by $PM_{10}$ pollution in cities upwind of this city on the same day and the previous day. $\rho_1$ and $\rho_2$ represent the spatial correlations of $PM_{10}$ concentrations. Our main hypothesis is to test whether $\rho_1 = \rho_2 = 0$, namely the null hypothesis that spatial spillover effects of $PM_{10}$ do not exist.[11]

$X_{i,ymd}$ includes weather, fuel prices, dummy variables for post-harvest seasons of crops, and dummy variables for weekends and national holidays. We consider a

[11] We also considered adding spatially and temporally-lagged $PM_{10}$ variables for more than one period as additional explanatory variables. We find that coefficient estimates of these additional variables are not statistically significant and coefficient estimates of other variables are close to our baseline estimates. For brevity, these results are not reported, but are available upon request.

comprehensive set of weather variables, including daily precipitation, sunshine duration, maximum temperature ($T_{\max}$), minimum temperature ($T_{\min}$), average wind speed, relative humidity and atmospheric pressure. Because private vehicles in China are usually powered with gasoline, we use gasoline price as an explanatory variable to control for the effects of vehicle emissions on city-average $PM_{10}$ concentrations. An increase in gasoline price is expected to reduce vehicle miles traveled and thus total fuel consumption, which in turn may reduce urban $PM_{10}$ concentrations. To reduce emissions from crop residue burning, Chinese governments at different levels have imposed bans on open-field burning of crop residues during post-harvest seasons. However, illicit burning of crop residues still occurs across China's agricultural heartland because it is a cheap way to remove crop residues from fields, while enhancing soil fertility. To control for the effects of farmers' illicit burning of crop residues on $PM_{10}$ pollution, we include dummies for the post-harvest seasons of three major crops in China, including corn, wheat and rice. $\beta$ reflects the effects of these local factors on city-average $PM_{10}$ concentrations.

### *4.2 Weighting scheme*

To estimate $\rho_1$ and $\rho_2$ in Eq. (1), the spatial weights matrices, including $\omega_{ij,ymd}$ and $\omega_{ij,ymd-1}$, must be specified. Atmospheric studies emphasize 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, we use three sources of information to specify our spatial weights matrices:

$$\omega_{ij,ymd} = \begin{cases} \frac{GDP_{j,y}}{f(d_{i,j})ws_{j,ymd}} & if\ g_{i,j} = wd_{j,ymd} \text{ and } \frac{d_{i,j}}{ws_{j,ymd}} \leq 24\ hours \\ 0 & otherwise \end{cases} \quad (2)$$

The first source of information is the geographical distance between the centroid of city *i* and the centroid of city *i's* upwind city *j*, denoted by $d_{i,j}$. The value of the weight assigned to city *j* by city *i* is negatively correlated with $d_{i,j}$. If city *j* is geographically close to city *i*, we assign a large weight to city *j*. Otherwise, a small weight will be assigned. Atmospheric studies suggest that the amount of air pollutants transported from a city to downwind areas of this city by wind may not be a linear function of distance. Rather, this transport process is highly complex and is expected to be a nonlinear function of distance. In the empirical analysis, we consider several functional forms, represented by $f(d_{i,j})$ in Eq. (2), to characterize this process and to examine the robustness of our results.

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 month *m* of year *y* (denoted by $wd_{j,ymd}$). In addition to distance, spatial interaction of PM is most likely to occur if there is sufficient air flow so that wind can carry $PM_{10}$ from city *j* to cities downwind of city *j*. Thus, we assign a positive weight to city *j* if there is wind blowing from city *j* toward city *i*, i.e., $g_{i,j} = wd_{j,ymd}$. For instance, if city *j* is located northeast of city *i*, the $PM_{10}$ concentration in city *i* on day *d* in month *m* of year *y* is affected by city *j*'s $PM_{10}$ concentration on the same day if and only if city *j* has a northeast wind blowing on that day. We use 16 cardinal directions to characterize $g_{i,j}$ and $wd_{j,ymd}$.

The third source of information is the wind speed in city *i*'s upwind cities, denoted by $ws_{j,ymd}$. The speed of wind affects horizontal movement of PM and determines how long it can take PM to travel from the origin city *j* to the destination city *i*. Atmospheric studies find that pollutant concentrations in cities downwind of city *j* are negatively correlated with the wind speed in city *j* (Ermak, 1977). Lastly, we multiply

$\frac{1}{f(d_{i,j}) ws_{j,ymd}}$ by GDP in city $j$ in year $y$, denoted by $GDP_{j,y}$, to capture the effect of city $j$'s emission strength on $PM_{10}$ concentrations in downwind cities.

When specifying $\omega_{ij,ymd}$, we assign positive weights to city $j$ if it takes less than 24 hours to transport $PM_{10}$ from city $j$ to city $i$. Using the same approach, we also specify $\omega_{ij,ymd-1}$. Here, $\omega_{ij,ymd-1}$ is specified differently from $\omega_{ij,ymd}$ in that, when specifying $\omega_{ij,ymd-1}$, we assign positive weights to city $j$ if it takes more than 24 hours but less than 48 hours to transport $PM_{10}$ from city $j$ to city $i$, $24\ hours < \frac{d_{i,j}}{ws_{j,ymd-1}} \leq 48\ hours$.

*4.3 Method of estimation*

When panel lengths are short and the number of "individuals" is large, the standard method is to apply GMM to estimate dynamic panel models with fixed individual effects,[12] while OLS estimates are inconsistent (Nickell, 1981). However, this inconsistency tends to be negligible when panel lengths are large (Deryugina and Hsiang, 2014). With daily observations, our panel has a large number of time periods. Moreover, using OLS allows us to account for spatial correlation and autocorrelation of the error terms, while avoiding using weak instruments, which is a common issue for GMM estimators (Roodman, 2009). Therefore, we use OLS to estimate Eq. (1), with standard errors clustered within province-year-month-day and within cities (see Cameron et al., 2011; Hsiang, 2010). The former (clustering standard errors within province-year-month-day) accounts for spatial correlation across cities within each province-year-month-day, while the latter (clustering standard errors within cities)

12 Another leading procedure estimating SDPD models is the (quasi) maximum likelihood estimation (MLE) (Lee and Yu, 2014).

accounts for serial correlation within each city. We also allow for the heteroscedasticity of the error terms.

## 5. Data

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

### *5.1 $PM_{10}$ data*

We use the approach introduced by Andrews (2008) to construct daily $PM_{10}$ concentrations for the 108 major cities included in our sample over the period 2009-2013, based on the daily air pollution index (API) reported by the Ministry of Environmental Protection (MEP). API is a composite index of $PM_{10}$, $SO_2$, and $NO_2$.[13] Daily concentrations of the three pollutants are recorded by monitoring stations in each city and are rescaled for ease of comparison. The pollutant that has the highest concentration on a day is identified as the "major pollutant" for that day. The MEP uses a piece-wise linear conversion formula to compute a city's daily average API based on the concentration of the "major pollutant" in that city. However, the MEP reported only daily average API and "major pollutants" for each city during our study period. Hence, daily $PM_{10}$ data can be retrieved only if $PM_{10}$ was reported as the "major pollutant" on a particular day, which leads to an unbalanced panel. In our sample, $PM_{10}$ accounts for more than 75% of the "major pollutants".

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

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

northwestern Beijing, for six weeks in 2008. They found that the self-measured $PM_{10}$ concentrations were about 30% higher than those reported by the Beijing Environmental Protection Bureau. Using daily air pollution data 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.[14] Chen et al. (2012) confirmed such API discontinuity, 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 for air quality in urban China and still provide useful information about air pollution in Chinese cities.

We select Beijing (located in northern China) and Chengdu (a major city located in western China) as two representative cities to get a sense of daily $PM_{10}$ co-movement between the two cities and their upwind cities. We plot daily $PM_{10}$ concentrations in 2012 for each of the two cities and their two upwind cities during the winter and summer monsoon seasons. Figure 2 shows that $PM_{10}$ concentrations between the two cities and their upwind cities are positive and statistically significant ($p < 1\%$). For instance, during the winter monsoon season, the correlation coefficients between Beijing and its two upwind cities are 0.32 and 0.26, while the correlation coefficients between Chengdu and its two upwind cities are 0.67 and 0.60. During the summer monsoon season, $PM_{10}$ correlations for the two cities and their upwind cities are also large and statistically significant ($p < 1\%$).

[14] That is because the number of "blue sky" days (a blue sky day is defined as a day for which the average API is below 100) was used as a measure for environmental performance of local officials by the central government.

*5.2 Weather data*

We gather weather data from the China Meteorological Data Sharing Service System, which records daily weather information for 820 weather stations in China. The fine-scale weather data set also contains coordinates of each weather station, enabling us to match weather data with our air pollution 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.

According to Ding (1994), the winter monsoon is defined as between November and March. The summer monsoon period differs substantially across regions in China. The summer monsoon in southern China typically starts in the middle of April and ends in September, while southerly winds dominate northern China in the middle of July and begin to weaken from August 10 (Ding, 1994). We define the summer monsoon as between July 15 and August 10, which is the time period during which southerly winds dominate the entire China's EMR. Figure 3 plots the distributions of wind direction during the monsoon seasons and verifies that the prevailing winds have been southerly (with cardinals of 6-12) during the summer monsoon season, and China's EMR is dominated by northerly winds during the winter monsoon season (with cardinals of 1-5 and 13-16).

*5.3 Other control variables*

We obtain gasoline prices from the National Development and Reform Commission (NDRC) for the sample period.[15] The NDRC is the nation's top economic planner, and it sets baseline fuel prices in China. State-owned retailers are

[15] See http://www.sdpc.gov.cn/zcfb/zcfbgg/index_2.html, last accessed on March 26, 2016.

allowed to adjust retail fuel prices within a tight 8% up or down band of the baseline prices. The frequency of fuel price adjustments ranges from days to weeks, depending on the fluctuations in international prices of crude oil. China has been revising the fuel pricing policy and changing the frequency of fuel price adjustments to better reflect the international prices of crude oil, but the pricing mechanism implemented by the NDRC is still not fully market-driven (Zhang and Xie, 2016). We collect province-level post-harvest seasons of corn, wheat and rice from the Ministry of Agriculture of China.[16]

*5.4 Summary statistics*

Table 1 reports summary statistics of key variables. With the daily specification for our observations, we have a total number of 47,881 and 9,713 observations during the winter and summer monsoon seasons, respectively. We find that all variables exhibit significant variability during the sample period.[17] From Figure 1, we find two apparent patterns: (*i*) average $PM_{10}$ concentrations in most cities during the winter monsoon season are significantly higher than that during the summer monsoon season; and (*ii*) there exist considerable variations in average $PM_{10}$ concentrations across Chinese cities. Table 2 shows that correlations of weather variables are generally significant ($p < 1\%$), suggesting that, to account for the simultaneous variations in weather variables, these weather variables should be incorporated in the regression analysis to minimize estimation biases originating from omitted variables.

[16] The Chinese language version of the website is available at http://202.127.42.157/moazzys/nongshi.aspx, last accessed on March 26, 2016.

[17] Based on the Augmented Dickey-Fuller (ADF), the Elliott-Rothenberg-Stock DF-GLS, and the Phillips-Perron (PP) test statistics, we find that $PM_{10}$ concentrations, weather variables, and gasoline price are stationary. For brevity, these test statistics are not reported here.

## 6. Baseline results

In this section, we report the baseline results based on the observations during the winter monsoon season in Table 3, while the corresponding results based on the sample during the summer monsoon season are summarized in Table 4. In each table, we conduct the spatial analysis of urban air pollution using three different model specifications. Specifically, in Model 1, we include only local factors, namely a temporally-lagged dependent variable, weather variables, gasoline price, and dummy variables for post-harvest seasons of rice, corn and wheat, as explanatory variables to examine the variations in city-average $PM_{10}$ concentrations during the sample period. In Model 2, we add "the spatially-lagged $PM_{10}$ variable" to examine whether a city's $PM_{10}$ concentration is affected by contemporaneous $PM_{10}$ transport from upwind cities. In Model 3, we incorporate "the spatially and temporally-lagged $PM_{10}$ variable" as an additional explanatory variable. The three model specifications incorporate weekend and holiday dummies and city-year-month fixed effects. In the baseline analysis, we specify $f(d_{i,j})$ in Eq. (2) as a linear function of distance, i.e., $f(d_{i,j}) = d_{i,j}$. This assumption will be relaxed in the robustness check section.

### *6.1 Temporal dependence of $PM_{10}$ concentrations*

Coefficient estimates of the temporally lagged $PM_{10}$ variable are positive and statistically significant ($p$ < 1%) in all three model specifications, indicating that city-average $PM_{10}$ concentrations are temporally correlated. Holding all else the same, if the average $PM_{10}$ level in a city on a given day increases by one unit during the winter monsoon season, the average $PM_{10}$ concentration for the same city on the following day is expected to increase by 0.43-0.46 units. The remaining portion (0.54-0.57 units) of the increase in $PM_{10}$ concentration is diluted by nature. The temporal dependence of $PM_{10}$ concentrations during the summer monsoon season is considerably smaller, at 0.31-0.32.

*6.2 Spatial spillovers of $PM_{10}$ pollution*

In Models 2 and 3, the coefficient estimates of "the spatially-lagged $PM_{10}$ variable" are positive and statistically significant ($p < 1\%$). The parameter estimate of this variable is 0.11-0.12 when the analysis is conducted using the winter monsoon sample and is 0.08 when the analysis is conducted using the summer monsoon sample. This provides strong evidence for the existence of spatial spillover effects of $PM_{10}$. With the linear specifications of the two models, the coefficient estimates of this variable can be interpreted as follows: for each unit increase in $PM_{10}$ concentrations in a city's upwind cities, the average $PM_{10}$ concentration in this city is expected to increase by 0.11-0.12 units during the winter monsoon season and by 0.08 during the summer monsoon season, holding all else the same.

Compared to the contemporaneous pollution spillover effects, the negative impacts on local air quality of the one-day lagged $PM_{10}$ pollution transported from upwind cities are much smaller. The coefficient estimate of "the spatially and temporally-lagged $PM_{10}$ variable" is insignificant for the summer monsoon sample. Although it is statistically significant ($p < 1\%$) for the winter monsoon sample, it is about 45% smaller than the coefficient estimate of "the spatially-lagged $PM_{10}$ variable". That probably is the case because, when $PM_{10}$ travels long distance and when wind speed is slow, most of the $PM_{10}$ from upwind cities will be diluted by natural ecosystems (Kalthoff et al., 2000).

*6.3 Effects of other local factors on $PM_{10}$ concentrations*

Coefficient estimates of the precipitation and wind speed variables are negative and statistically significant ($p < 1\%$), and remain fairly comparable across different model specifications. This suggests that increased precipitation and strong winds can effectively reduce ground-level $PM_{10}$ concentrations and improve urban air quality. These findings are in agreement with the well-established literature on atmospheric pollution (see Arya, 1999).

Temperature effects on $PM_{10}$ concentrations differ over time during a day. The parameter estimate of $T_{\mathrm{min}}$ is found to be negative and statistically significant ($p < 1\%$) for the winter monsoon sample, suggesting that higher $T_{\mathrm{min}}$ can reduce city-average $PM_{10}$ concentrations. The mechanism behind this finding is simple. Studies on atmospheric pollution have discovered 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 $PM_{10}$ away from the surface and thus reduce ground-level $PM_{10}$ concentrations (Arya, 1999). The coefficient estimate of $T_{\mathrm{min}}$ has a positive sign but it is insignificant for the summer monsoon sample. The coefficient estimate of $T_{\mathrm{max}}$ is found to be positive and statistically significant ($p < 1\%$). While $T_{\mathrm{min}}$ typically occurs before sunrise, $T_{\mathrm{max}}$ usually occurs during the early to middle afternoon. Human activities, such as construction and driving for recreation, are expected to be highest during the early to middle afternoon, and may generate $PM_{10}$ that is not captured by our explanatory variables. That may explain the positive coefficient estimate of the $T_{\mathrm{max}}$ variable. Coefficient estimates of other weather variables, including sunshine hours, relative humidity and atmospheric pressure, are consistent with well-established atmospheric evidence (Seinfeld and Pandis, 2006).

Parameter estimates of other control variables have expected signs and statistical significance. Coefficient estimates of the dummy variables for post-harvest seasons of rice, corn and wheat are insignificant, possibly because post-harvest seasons of the three crops are collected at provincial scale and the city-year-month fixed effects may have absorbed some of the effects of burning residues on $PM_{10}$ concentrations. The coefficient estimate of gasoline price is negative and statistically significant for the winter monsoon sample, suggesting that by reducing fuel consumption increased gasoline prices have effectively improved air quality during the winter months. The coefficient estimate of this variable is insignificant for the summer monsoon sample, possibly because car travel during the summer months is more responsive to changes in income than to changes in fuel prices (Dargay and Gately, 1999).

## 7. Robustness checks

The results presented above regarding the impacts of various factors on ambient $PM_{10}$ concentrations make intuitive sense. But how robust are they? In this section, we examine the sensitivity of our results in nine different scenarios. For brevity, we summarize estimated pollution spillover effects (the sum of the point estimates of “the spatially-lagged $PM_{10}$ variable” and “the spatially and temporally-lagged $PM_{10}$ variable) and their 95% confidence bands across various scenarios in Figure 4.[18]

### *7.1 Results by spatial weights matrix and econometric estimation strategy*

The first set of robustness checks addresses the sensitivity of our results to variations in spatial weights matrices and econometric estimation strategies. In

[18] Across the various scenarios that we considered, coefficient estimates of other control variables are fairly close to our baseline estimates. For brevity, they are not reported.

Scenarios (1)-(3), we consider three nonlinear forms of distance function suggested by Ermak (1977) to construct our spatial weights matrix. Specifically, we consider a quadratic distance function $f(d_{i,j}) = d_{i,j} + d_{i,j}^2$ in Scenario (1), a square root distance function $f(d_{i,j}) = d_{i,j}^{0.5}$ in Scenario (2), and an exponential distance function $f(d_{i,j}) = \exp(d_{i,j})$ in Scenario (3). In Scenario (4), we replicate the above analysis by estimating standard errors that are clustered within cities and within region-year-month-days (rather than within cities and within city-year-month-days in the baseline analysis). We consider this scenario mainly due to the concern that the error terms may be correlated because a shock occurring in a region on a given day may affect $PM_{10}$ concentrations for all cities located in that region on that day. In Scenario (5), we use city-year-season fixed effects and month fixed effects to control for the unobserved factors (rather than city-year-month fixed effects in the baseline analysis). We find that estimated pollution spillover effects in these five scenarios are almost identical to our baseline estimates, suggesting that our results are robust to variations in spatial weights matrices and econometric estimation strategies.

### *7.2 Results by variable and sample*

Neighboring cities are likely to experience similar shocks due to changes in regional business/pollution cycles and meteorological conditions. To separate the pollution spillovers caused by idiosyncratic changes in wind direction from these regional shocks, we add an additional variable in Eq. (1) in Scenario (6). This new variable is another weighted average of $PM_{10}$ concentrations in nearby cities, where weights are based solely on distance between cities but not on wind direction. This variable is expected to control for regional shocks because of changes in regional business/pollution cycles and meteorological conditions, which are most likely to be correlated across nearby cities and are unrelated to wind direction. As shown in Figure 4, we find that the estimates of the pollution spillover effects are still positive and statistically significant ($p < 1\%$), but they are about 42-49% smaller than our baseline estimates.

Although the prevailing wind directions are northerly during the winter monsoon season and southerly during the summer monsoon season, wind directions in some cities during the monsoon seasons still occasionally change (see Figure 3). In Scenario (7), we further restrict our sample by dropping observations that are not strictly following prevailing wind directions during the two monsoon seasons. Estimated pollution spillover effects in this scenario are statistically significant ($p < 1\%$), and their magnitudes are broadly consistent with our baseline estimates.

*7.3 Results by terrain feature*

Lastly, we examine the role of terrain features in affecting regional spillovers of $PM_{10}$ pollution in Scenarios (8) and (9). A flat terrain facilitates unobstructed movement of wind and thus air pollution. China has four major plains, including Northeast China Plain, North China Plain, Yangtze Plain and Guanzhong Plain. We divide our sample into two subsamples based on whether a city is located in plain or non-plain regions. As expected, we find that estimated spillover effects in plain regions are considerably (24-37%) larger than the baseline estimates, while estimated spillover effects in non-plain regions are substantially (37-58%) smaller than our baseline estimates[19].

[19] The estimated spillover effect in non-plain regions during the summer monsoon season is statistically insignificant.

## 8. Assessment of the upwind impacts

The results presented above show how various factors affect city-average $PM_{10}$ concentrations and their statistical significance. In this section, we estimate the percentage contributions of $PM_{10}$ transported from upwind cities to local $PM_{10}$ concentrations for each of the cities included in our sample. To achieve this goal, we first estimate our baseline Model 3 for each city as a time series regression analysis, and obtain city-specific parameter estimates of $\rho_1$ and $\rho_2$. We then compute $\theta_i$ for city *i*:

$$\theta_i = \frac{\sum_{j \neq i}^{J} E(PM_j)}{E(PM_i)} \tag{3}$$

where $E(PM_i)$ denotes the predicted $PM_{10}$ concentration for city *i* and $\sum_{j \neq i}^{J} E(PM_j)$ represents the sum of the $PM_{10}$ transported from *J* upwind cities of city *i* on days *d* and *d-1*. When calculating $E(PM_i)$, we first obtain city-specific predicted values of $PM_{i,ymd}$ for day *d* in month *m* of year *y*. We then compute the average of the predicted values of $PM_{i,ymd}$ over time to get $E(PM_i)$. Similarly, we use city-specific parameter estimates of $\rho_1$ and $\rho_2$, multiplied by sample means of $\sum_{j \neq i}^{J} \omega_{ij,ymd} PM_{j,ymd}$ and $\sum_{j \neq i}^{J} \omega_{ij,ymd-1} PM_{j,ymd-1}$, respectively, to compute $\sum_{j \neq i}^{J} E(PM_j)$. Hence, $\theta_i$ measures the "average" contribution of $PM_{10}$ transported from upwind cities to city *i*'s $PM_{10}$ concentrations.

Figure 5 shows that there exist large variations in estimated $\theta_i$ across cities, ranging from 0% to 30% during the winter monsoon season and from 0% to 26% during the summer monsoon season. Of the cities included in the sample, we find that the cities located in the North China Plain and Yangtze River Delta regions are most affected by $PM_{10}$ pollution from upwind cities. These are expected results because: (*i*) the two regions have a large number of adjacent cities and (*ii*) the two regions have relatively flat terrain that facilitates pollution diffusion across regions. The estimated percentage contributions of $PM_{10}$ pollution from upwind cities are comparable with the findings reported in Guo et al. (2014) and Liu et al. (2016) that focus on cities in the North China Plain region.

Most of the cities that are least affected by $PM_{10}$ pollution from upwind cities during the winter monsoon season are located in mountainous areas. Their local terrains can effectively prevent wind from carrying air pollutants from other regions. During the summer monsoon season, the cities with smallest upwind impacts are located in Central China, which are expected given that the prevailing wind directions are southerly during the summer months and the cities located in southern China have much lower $PM_{10}$ levels relative to cities in northern China (see Figure 1).

## 9. Conclusions and discussion

In this paper, we exploit spatial and temporal variations in $PM_{10}$ concentrations for major cities located in China's EMR during the East Asian monsoon seasons to examine the effects of various local and neighboring factors on $PM_{10}$ concentrations in Chinese cities. To fully incorporate the spatial and temporal dynamics of $PM_{10}$ concentrations, we develop a dynamic spatial panel model. The spatial weights matrix constructed in the model considers not only geographical distance between cities, but also wind direction, wind speed, and emission strength in upwind 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 over time. In contrast to the approaches used by atmospheric studies, findings based on our regression framework remain remarkably robust to locations, econometric estimation strategies, data and variables.

Our regression results provide strong evidence of the existence of spatial spillover effects of air pollution. Coefficient estimates of weather variables are consistent with the findings presented in the atmospheric pollution literature. Other variables have intuitive signs and magnitudes as well. For example, city-average $PM_{10}$ concentrations are temporally correlated, and higher gasoline prices help to improve air quality. We also find that the percentage contributions of pollution from upwind cities to local $PM_{10}$ levels vary across regions, with cities located in the North China Plain and Yangtze River Delta regions most affected by pollution from upwind cities.

Our findings have important public policy implications for the effective design of China's air pollution control policies. Given the existence of transboundary air pollution across regions, China's widely-adopted strategy of relocating large-scale and heavily polluting factories to suburbs or neighboring cities will not be effective. To effectively abate transboundary air pollution, pollution control policies must be coordinated between cities and provinces to address this negative externality. Our findings also support the idea that China should adopt a version of the US EPA's Good Neighbor Rule, which is designed to address interstate transport of air pollution.

Several caveats apply. First, because daily $PM_{10}$ data used in the sample are not continuous, we may have underestimated the true spatial spillover effects of $PM_{10}$. Second, our sample includes only 108 major Chinese cities in the EMR. While we investigate the spatial correlations of $PM_{10}$ among these major cities, there are many small and medium-size cities located between these major cities. $PM_{10}$ generated in those cities could be transported by wind to the major cities in the sample. As a result, our estimated spatial spillover effects could be smaller or larger than the actual estimates. The last major caveat is that we cannot conduct a cost-benefit analysis to quantify the costs and benefits of abating $PM_{10}$. On the cost side, there exist a number of options to reduce $PM_{10}$ emissions, with marginal abatement costs varying by city and by abatement option. The relationship between emissions and concentrations is quite complex and varies across locations (Lanigan, 1993). Thus, it is quite difficult to predict how $PM_{10}$ concentrations will change when emission levels change. On the benefit side, it is difficult to estimate the benefits stemming from reduced $PM_{10}$ concentrations, because the benefits depend not only on reduced $PM_{10}$ concentrations, but also on initial $PM_{10}$ levels. Moreover, estimating the benefits due to reduced $PM_{10}$ concentrations would require us to project the potential reduction of the number of days when activity is restricted because of air pollution, as well as estimates on reduced health costs and increased output from increased work time, all of which vary by city. We can conclude by pointing to a multiplier effect of pollution abatement. If all cities lower their $PM_{10}$ concentrations by one unit, average $PM_{10}$ concentrations in Chinese cities can decrease by up to 1.7 units during the winter monsoon season and by up to 1.1 units during the summer monsoon season.

## References:

Allen, G., Sioutas, C., Koutrakis, P., Reiss, R., Lurmann, F.W., Roberts, P.T., 1997. Evaluation of the TEOM® Method for Measurement of Ambient Particulate Mass in Urban Areas. Journal of the Air & Waste Management Association 47, 682–689. doi:10.1080/10473289.1997.10463923

Andrews, S.Q., 2008. Inconsistencies in air quality metrics: "Blue Sky" days and PM 10 concentrations in Beijing. Environmental Research Letters 3, 34009. doi:10.1088/1748-9326/3/3/034009

Anselin, L., Bera, A., 1997. Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics, in: Ullah, A., Giles, D. (Eds.), Handbook of Applied Economic Statistics. Marcel Dekker, New York.

Arya, S., 1999. Air Pollution Meteorology and Dispersion. Oxford University Press.

Brozović, N., Sunding, D.L., Zilberman, D., 2010. On the spatial nature of the groundwater pumping externality. Resource and Energy Economics 32, 154–164. doi:10.1016/j.reseneeco.2009.11.010

Cameron, A.C., Gelbach, J.B., Miller, D.L., 2011. Robust Inference With Multiway Clustering. Journal of Business & Economic Statistics 29, 238–249. doi:10.1198/jbes.2010.07136

Capaldo, K., Pilinis, C., Pandis, S.N., 2000. A computationally efficient hybrid approach for dynamic gas/aerosol transfer in air quality models. Atmospheric Environment 34, 3617–3627. doi:10.1016/S1352-2310(00)00092-3

Chakravorty, U., Umetsu, C., 2003. Basinwide water management: a spatial model. Journal of Environmental Economics and Management 45, 1–23. doi:10.1016/S0095-0696(02)00012-8

Chan, C.K., Yao, X., 2008. Air pollution in mega cities in China. Atmospheric Environment 42, 1–42. doi:10.1016/j.atmosenv.2007.09.003

Chay, K.Y., Greenstone, M., 2005. Does Air Quality Matter? Evidence from the Housing Market. Journal of Political Economy 113, 376–424. doi:10.1086/427462

Chen, D.S., Cheng, S.Y., Liu, L., Chen, T., Guo, X.R., 2007. An integrated MM5–CMAQ modeling approach for assessing trans-boundary PM10 contribution to the host city of 2008 Olympic summer games—Beijing, China. Atmospheric Environment 41, 1237–1250. doi:10.1016/j.atmosenv.2006.09.045

Chen, Y., Ebenstein, A., Greenstone, M., Li, H., 2013a. Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. Proceedings of the National Academy of Sciences 110, 12936–12941. doi:10.1073/pnas.1300018110

Chen, Y., Jin, G.Z., Kumar, N., Shi, G., 2013b. The promise of Beijing: Evaluating the impact of the 2008 Olympic Games on air quality. Journal of Environmental Economics and Management 66, 424–443. doi:10.1016/j.jeem.2013.06.005

Chen, Y., Jin, G.Z., Kumar, N., Shi, G., 2012. Gaming in air pollution data lessons from China, B.E. Journal of Economic Analysis and Policy. doi:10.1515/1935-1682.3227

Cheng, Z., Jiang, J., Fajardo, O., Wang, S., Hao, J., 2013. Characteristics and health impacts of particulate matter pollution in China (2001–2011). Atmospheric Environment 65, 186–194. doi:10.1016/j.atmosenv.2012.10.022

Dargay, J., Gately, D., 1999. Income's effect on car and vehicle ownership, worldwide: 1960–2015. Transportation Research Part A: Policy and Practice 33, 101–138. doi:10.1016/S0965-8564(98)00026-3

Deryugina, T., Hsiang, S.M., 2014. Does the Environment Still Matter? Daily Temperature and Income in the United States. National Bureau of Economic Research Working Paper Series No. 20750. doi:10.3386/w20750
Ding, Y., 1994. Monsoons over China. Springer Netherlands.
Duce, R.A., Unni, C.K., Ray, B.J., Prospero, J.M., Merrill, J.T., 1980. Long-Range Atmospheric Transport of Soil Dust from Asia to the Tropical North Pacific: Temporal Variability. Science 209, 1522–1524.
Ermak, D.L., 1977. An analytical model for air pollutant transport and deposition from a point source. Atmospheric Environment (1967) 11, 231–237. doi:10.1016/0004-6981(77)90140-8
Foster-Wittig, T.A., Thoma, E.D., Albertson, J.D., 2015. Estimation of point source fugitive emission rates from a single sensor time series: A conditionally-sampled Gaussian plume reconstruction. Atmospheric Environment 115, 101–109. doi:10.1016/j.atmosenv.2015.05.042
Ghanem, D., Zhang, J., 2014. “Effortless Perfection:” Do Chinese cities manipulate air pollution data? Journal of Environmental Economics and Management 68, 203–225. doi:http://dx.doi.org/10.1016/j.jeem.2014.05.003
Goetz, R.U., Zilberman, D., 2000. The dynamics of spatial pollution: The case of phosphorus runoff from agricultural land. Journal of Economic Dynamics and Control 24, 143–163. doi:10.1016/S0165-1889(98)00067-0
Griffin, R.C., Bromley, D.W., 1982. Agricultural Runoff as a Nonpoint Externality: A Theoretical Development. American Journal of Agricultural Economics 64, 547–552.
Guo, S., Hu, M., Zamora, M.L., Peng, J., Shang, D., Zheng, J., Du, Z., Wu, Z., Shao, M., Zeng, L., Molina, M.J., Zhang, R., 2014. Elucidating severe urban haze formation in China. Proceedings of the National Academy of Sciences of the United States of America 111, 17373–8. doi:10.1073/pnas.1419604111
Hsiang, S.M., 2010. Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. Proceedings of the National Academy of Sciences of the United States of America 107, 15367–72. doi:10.1073/pnas.1009510107
Jia, R., Ku, H., 2016. Is China’s Pollution the Culprit for the Choking of South Korea ? Evidence from the Asian Dust. Working paper.
Kallos, G., Kotroni, V., Lagouvardos, K., Papadopoulos, A., 1998. On the Long-Range transport of air pollutants from Europe to Africa. Geophysical Research Letters 25, 619–622. doi:10.1029/97GL03317
Kalthoff, N., Horlacher, V., Corsmeier, U., Volz-Thomas, A., Kolahgar, B., Geiß, H., Möllmann-Coers, M., Knaps, A., 2000. Influence of valley winds on transport and dispersion of airborne pollutants in the Freiburg-Schauinsland area. Journal of Geophysical Research: Atmospheres 105, 1585–1597. doi:10.1029/1999JD900999
Katz, M., 1969. Measurement of air pollutants: Guide to selection of methods. World Health Organization, Geneva.
Kim, B., Park, S., 2001. Transport and evolution of a winter-time Yellow sand observed in Korea. Atmospheric Environment 35, 3191–3201. doi:10.1016/S1352-2310(00)00469-6
Kuwayama, Y., Brozović, N., 2013. The regulation of a spatially heterogeneous externality: Tradable groundwater permits to protect streams. Journal of Environmental Economics and Management 66, 364–382. doi:10.1016/j.jeem.2013.02.004

Lanigan, S., 1993. Valuing the Unknown: Cost-Benefit Analysis and Air Pollution. Oxford Institute for Energy Studies.
Lee, L., Yu, J., 2014. Efficient GMM estimation of spatial dynamic panel data models with fixed effects. Journal of Econometrics 180, 174–197. doi:http://dx.doi.org/10.1016/j.jeconom.2014.03.003
Lin, T.-H., 2001. Long-range transport of yellow sand to Taiwan in Spring 2000: observed evidence and simulation. Atmospheric Environment 35, 5873–5882. doi:10.1016/S1352-2310(01)00392-2
Liu, J., Mauzerall, D.L., Chen, Q., Zhang, Q., Song, Y., Peng, W., Klimont, Z., Qiu, X., Zhang, S., Hu, M., Lin, W., Smith, K.R., Zhu, T., 2016. Air pollutant emissions from Chinese households: A major and underappreciated ambient pollution source. Proceedings of the National Academy of Sciences . doi:10.1073/pnas.1604537113
Luechinger, S., 2009. Valuing Air Quality Using the Life Satisfaction Approach*. The Economic Journal 119, 482–515. doi:10.1111/j.1468-0297.2008.02241.x
Mayer, H., 1999. Air pollution in cities. Atmospheric Environment 33, 4029–4037. doi:10.1016/S1352-2310(99)00144-2
Mishra, V.K., Padmanabhamutry, B., 2003. Performance evaluation of CALINE3, CAL3QHC and PART5 in predicting lead concentration in the atmosphere over Delhi. Atmospheric Environment 37, 3077–3089. doi:10.1016/S1352-2310(03)00272-3
NBS, 2012. China Statistical Database.
Nickell, S., 1981. Biases in Dynamic Models with Fixed Effects. Econometrica 49, 1417–1426. doi:10.2307/1911408
Nieuwenhuijsen, M.J., Gómez-Perales, J.E., Colvile, R.N., 2007. Levels of particulate air pollution, its elemental composition, determinants and health effects in metro systems. Atmospheric Environment 41, 7995–8006. doi:10.1016/j.atmosenv.2007.08.002
Pankow, J.F., Storey, J.M.E., Yamasaki, H., 1993. Effects of relative humidity on gas/particle partitioning of semivolatile organic compounds to urban particulate matter. Environmental Science & Technology 27, 2220–2226. doi:10.1021/es00047a032
Parrington, J.R., Zoller, W.H., Aras, N.K., 1983. Asian Dust: Seasonal Transport to the Hawaiian Islands. Science 220, 195–197.
Pfeiffer, L., Lin, C.-Y.C., 2012. Groundwater pumping and spatial externalities in agriculture. Journal of Environmental Economics and Management 64, 16–30. doi:10.1016/j.jeem.2012.03.003
Queen, A., Zhang, Y., 2008. Examining the sensitivity of MM5–CMAQ predictions to explicit microphysics schemes and horizontal grid resolutions, Part II—PM concentrations and wet deposition predictions. Atmospheric Environment 42, 3856–3868. doi:10.1016/j.atmosenv.2007.12.066
Queen, A., Zhang, Y., Gilliam, R., Pleim, J., 2008. Examining the sensitivity of MM5–CMAQ predictions to explicit microphysics schemes and horizontal grid resolutions, Part I—Database, evaluation protocol, and precipitation predictions. Atmospheric Environment 42, 3842–3855. doi:10.1016/j.atmosenv.2007.12.067
Roodman, D., 2009. How to do xtabond2: An introduction to difference and system GMM in Stata. Stata Journal 9, 86–136.
Seinfeld, J.H., Pandis, S.N., 2006. Atmospheric Chemistry and Physics: From Air Pollution to Climate Change, 2nd Editio. ed. ohn Wiley & Sons, New York.
Sigman, H., 2002. International Spillovers and Water Quality in Rivers: Do Countries

Free Ride? American Economic Review 92, 1152–1159. doi:10.1257/00028280260344687
Streets, D.G., Fu, J.S., Jang, C.J., Hao, J., He, K., Tang, X., Zhang, Y., Wang, Z., Li, Z., Zhang, Q., Wang, L., Wang, B., Yu, C., 2007. Air quality during the 2008 Beijing Olympic Games. Atmospheric Environment 41, 480–492. doi:10.1016/j.atmosenv.2006.08.046
Tsunogai, S., Kondo, T., 1982. Sporadic transport and deposition of continental aerosols to the Pacific Ocean. Journal of Geophysical Research 87, 8870. doi:10.1029/JC087iC11p08870
Viard, V.B., Fu, S., 2015. The effect of Beijing's driving restrictions on pollution and economic activity. Journal of Public Economics 125, 98–115. doi:10.1016/j.jpubeco.2015.02.003
Wang, L., Xu, J., Qin, P., 2014. Will a driving restriction policy reduce car trips?—The case study of Beijing, China. Transportation Research Part A: Policy and Practice 67, 279–290. doi:http://dx.doi.org/10.1016/j.tra.2014.07.014
Wang, W., Primbs, T., Tao, S., Simonich, S.L.M., 2009. Atmospheric Particulate Matter Pollution during the 2008 Beijing Olympics. Environmental Science & Technology 43, 5314–5320. doi:10.1021/es9007504
Won Kim, C., Phipps, T.T., Anselin, L., 2003. Measuring the benefits of air quality improvement: a spatial hedonic approach. Journal of Environmental Economics and Management 45, 24–39. doi:10.1016/S0095-0696(02)00013-X
Yang, G., Wang, Y., Zeng, Y., Gao, G.F., Liang, X., Zhou, M., Wan, X., Yu, S., Jiang, Y., Naghavi, M., Vos, T., Wang, H., Lopez, A.D., Murray, C.J.L., 2013. Rapid health transition in China, 1990-2010: findings from the Global Burden of Disease Study 2010. Lancet (London, England) 381, 1987–2015. doi:10.1016/S0140-6736(13)61097-1
Zhang, J., Mauzerall, D.L., Zhu, T., Liang, S., Ezzati, M., Remais, J. V, 2010. Environmental health in China: progress towards clean air and safe water. Lancet (London, England) 375, 1110–9. doi:10.1016/S0140-6736(10)60062-1
Zhang, J., Xie, M., 2016. China's oil product pricing mechanism: What role does it play in China's macroeconomy? China Economic Review 38, 209–221. doi:10.1016/j.chieco.2016.02.002
Zhang, R., Jing, J., Tao, J., Hsu, S.-C., Wang, G., Cao, J., Lee, C.S.L., Zhu, L., Chen, Z., Zhao, Y., Shen, Z., 2013. Chemical characterization and source apportionment of $PM_{2.5}$ in Beijing: seasonal perspective. Atmospheric Chemistry and Physics 13, 7053–7074. doi:10.5194/acp-13-7053-2013
Zhao, L., Gallagher, K.S., 2007. Research, development, demonstration, and early deployment policies for advanced-coal technology in China. Energy Policy 35, 6467–6477. doi:10.1016/j.enpol.2007.08.017
Zhou, L.-T., 2011. Impact of East Asian winter monsoon on rainfall over southeastern China and its dynamical process. International Journal of Climatology 31, 677–686. doi:10.1002/joc.2101

**Table 1. Descriptive statistics**

| Variable | Unit | Monsoon Season | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| $PM_{10}$ concentration | μg/m$^3$ | Winter | 101.2 | 60.6 | 5.9 | 600.0 |
| | | Summer | 62.0 | 30.7 | 9.8 | 361.9 |
| Precipitation | 0.1 mm | Winter | 13.7 | 49.2 | 0.0 | 3204.0 |
| | | Summer | 65.9 | 177.7 | 0.0 | 2670.0 |
| Sunshine duration | 0.1 hour | Winter | 45.2 | 38.3 | 0.0 | 121.0 |
| | | Summer | 62.3 | 42.9 | 0.0 | 145.0 |
| $T_{max}$ | 0.1 ℃ | Winter | 109.2 | 89.7 | -256.0 | 370.0 |
| | | Summer | 310.2 | 39.2 | 125.0 | 428.0 |
| $T_{min}$ | 0.1 ℃ | Winter | 26.3 | 93.6 | -352.0 | 253.0 |
| | | Summer | 233.6 | 33.8 | 107.0 | 326.0 |
| Average wind speed | 0.1 m/s | Winter | 24.0 | 15.8 | 0.0 | 203.0 |
| | | Summer | 21.8 | 12.2 | 0.0 | 131.0 |
| Atmospheric pressure | 0.1hPa | Winter | 9869.2 | 546.5 | 7776.0 | 10431.0 |
| | | Summer | 9703.1 | 503.0 | 7892.0 | 10147.0 |
| Relative humidity | 1% | Winter | 66.5 | 18.5 | 10.0 | 100.0 |
| | | Summer | 77.6 | 10.6 | 34.0 | 100.0 |
| Gasoline price | Yuan/ton | Winter | 8514.6 | 937.1 | 6320.0 | 10380.0 |
| | | Summer | 8610.9 | 728.0 | 7250.0 | 9780.0 |

*Notes*: The sample includes 108 cities from 2009 to 2013. $N$=47,881 during the winter monsoon season and $N$=9,713 during the summer monsoon season.

**Table 2a. Correlations of weather variables during the winter monsoon season**

| | Precipitation | Sunshine duration | $T_{max}$ | $T_{min}$ | Average wind speed | Atmospheric pressure |
|---|---|---|---|---|---|---|
| Sunshine duration | -0.281*** | - | | | | |
| $T_{max}$ | -0.149*** | 0.313*** | - | | | |
| $T_{min}$ | 0.039*** | -0.215*** | 0.640*** | - | | |
| Average wind speed | 0.117*** | -0.040*** | -0.100*** | 0.021*** | - | |
| Atmospheric pressure | -0.093*** | 0.124*** | -0.515*** | -0.508*** | 0.012*** | - |
| Relative humidity | 0.302*** | -0.565*** | -0.138*** | 0.170*** | -0.144*** | -0.224*** |

*Notes*: The Pearson's correlation coefficients of weather variables, after removing weather station and year fixed effects, are reported in the table. *N*=47,881.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 2b. Correlations of weather variables during the summer monsoon season**

| | Precipitation | Sunshine duration | $T_{max}$ | $T_{min}$ | Average wind speed | Atmospheric pressure |
|---|---|---|---|---|---|---|
| Sunshine duration | -0.368*** | - | | | | |
| $T_{max}$ | -0.334*** | 0.678*** | - | | | |
| $T_{min}$ | -0.212*** | 0.125*** | 0.502*** | - | | |
| Average wind speed | 0.146*** | -0.013 | -0.025** | 0.166*** | - | |
| Atmospheric pressure | -0.168*** | 0.056*** | -0.153*** | -0.236*** | -0.215*** | - |
| Relative humidity | 0.406*** | -0.689*** | -0.700*** | -0.326*** | -0.081*** | -0.005 |

*Notes*: The Pearson's correlation coefficients of weather variables, after removing weather station and year fixed effects, are reported in the table. *N*=9,713
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 3. Baseline results: Winter monsoon (dependent variable: $PM_{10}$ concentration)**

| Variables | Model 1: Local factors only | Model 2: Add spatial $PM_{10}$ | Model 3: Add lagged spatial $PM_{10}$ |
|---|---|---|---|
| Temporally-lagged $PM_{10}$ | 0.458*** | 0.446*** | 0.430*** |
| | (0.012) | (0.013) | (0.013) |
| Spatially-lagged $PM_{10}$ | | 0.116*** | 0.111*** |
| | | (0.011) | (0.010) |
| Spatially and temporally-lagged $PM_{10}$ | | | 0.061*** |
| | | | (0.009) |
| Precipitation | -0.103*** | -0.101*** | -0.101*** |
| | (0.016) | (0.015) | (0.015) |
| Sunshine duration | -0.172*** | -0.159*** | -0.158*** |
| | (0.021) | (0.020) | (0.020) |
| $T_{\max}$ | 0.278*** | 0.271*** | 0.278*** |
| | (0.018) | (0.018) | (0.017) |
| $T_{\min}$ | -0.135*** | -0.135*** | -0.141*** |
| | (0.022) | (0.022) | (0.022) |
| Average wind speed | -0.384*** | -0.429*** | -0.448*** |
| | (0.054) | (0.060) | (0.062) |
| Atmospheric pressure | -0.056*** | -0.045*** | -0.045*** |
| | (0.013) | (0.012) | (0.012) |
| Relative humidity | -0.022 | 0.003 | 0.019 |
| | (0.058) | (0.055) | (0.054) |
| Gasoline price | -0.005** | -0.006** | -0.006** |
| | (0.003) | (0.003) | (0.003) |
| Post-harvest season of rice | -0.287 | -0.034 | 0.377 |
| | (2.466) | (2.392) | (2.335) |
| $R^2$ | 0.310 | 0.326 | 0.332 |

*Notes*: City-year-month fixed effects and dummy variables for weekends and national holidays are included in all model specifications. Dummy variables for post-harvest seasons of corn and wheat are omitted because the harvest of the two crops does not occur during the winter monsoon season. Robust standard errors are in parentheses, adjusted for spatial correlation, autocorrelation, and heteroscedasticity of the error terms. *N*=47,881.

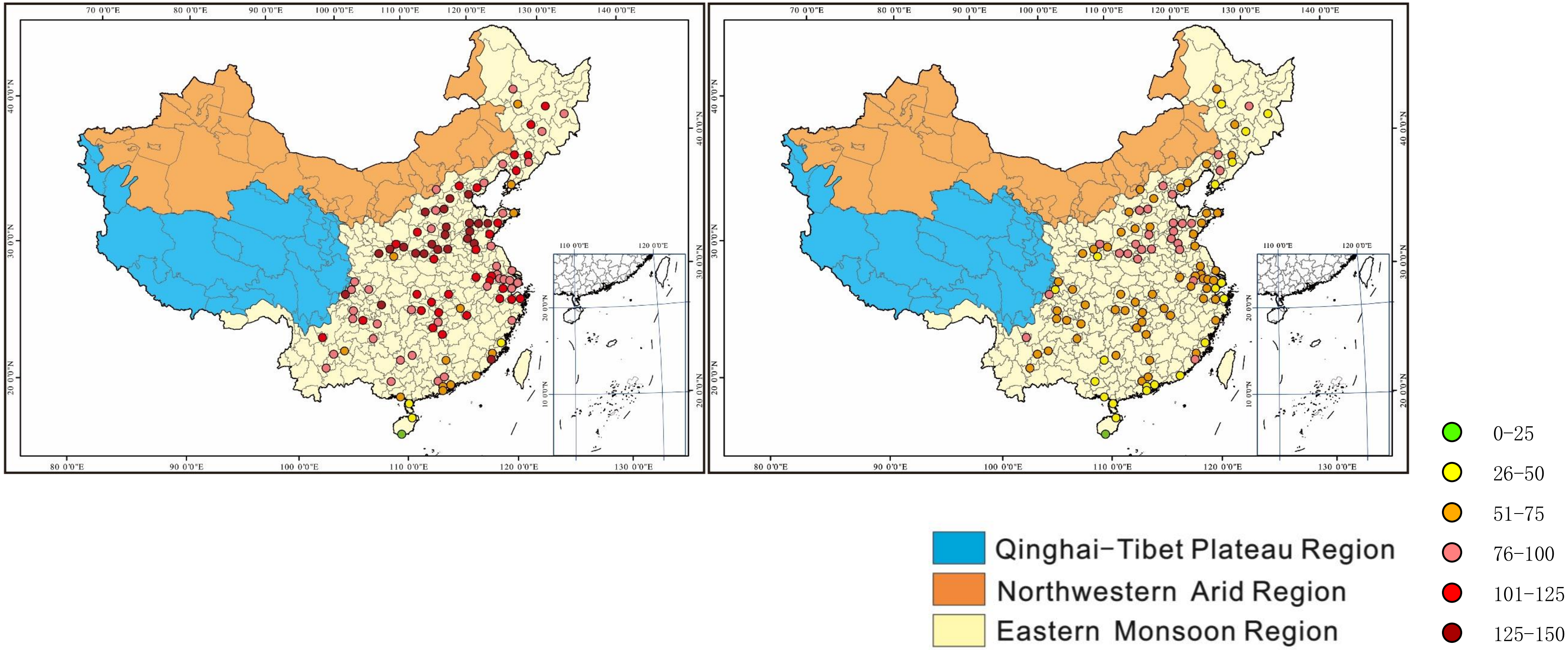
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 4. Baseline results: Summer monsoon (dependent variable: $PM_{10}$ concentration)**

| Variables | Model 1: Local factors only | Model 2: Add spatial $PM_{10}$ | Model 3: Add lagged spatial $PM_{10}$ |
|---|---|---|---|
| Temporally-lagged $PM_{10}$ | 0.321*** | 0.315*** | 0.313*** |
| | (0.020) | (0.020) | (0.019) |
| Spatially-lagged $PM_{10}$ | | 0.082*** | 0.082*** |
| | | (0.013) | (0.013) |
| Spatially and temporally- lagged $PM_{10}$ | | | 0.015 |
| | | | (0.011) |
| Precipitation | -0.011*** | -0.012*** | -0.012*** |
| | (0.002) | (0.002) | (0.002) |
| Sunshine duration | -0.143*** | -0.137*** | -0.136*** |
| | (0.022) | (0.022) | (0.022) |
| $T_{max}$ | 0.340*** | 0.329*** | 0.329*** |
| | (0.033) | (0.033) | (0.033) |
| $T_{min}$ | 0.025 | 0.022 | 0.022 |
| | (0.031) | (0.031) | (0.031) |
| Average wind speed | -0.257*** | -0.265*** | -0.267*** |
| | (0.043) | (0.044) | (0.044) |
| Atmospheric pressure | 0.017 | 0.021 | 0.022 |
| | (0.018) | (0.018) | (0.018) |
| Relative humidity | 0.139 | 0.136 | 0.136 |
| | (0.088) | (0.087) | (0.086) |
| Gasoline price | 0.004 | 0.004 | 0.003 |
| | (0.005) | (0.005) | (0.005) |
| Post-harvest season of rice | -1.483 | -1.340 | -1.340 |
| | (1.627) | (1.564) | (1.561) |
| Post-harvest season of corn | -2.354 | -1.906 | -1.777 |
| | (2.817) | (2.709) | (2.715) |
| Post-harvest season of wheat | 4.305 | 4.695 | 4.610 |
| | (2.706) | (2.871) | (2.945) |
| $R^2$ | 0.215 | 0.225 | 0.225 |

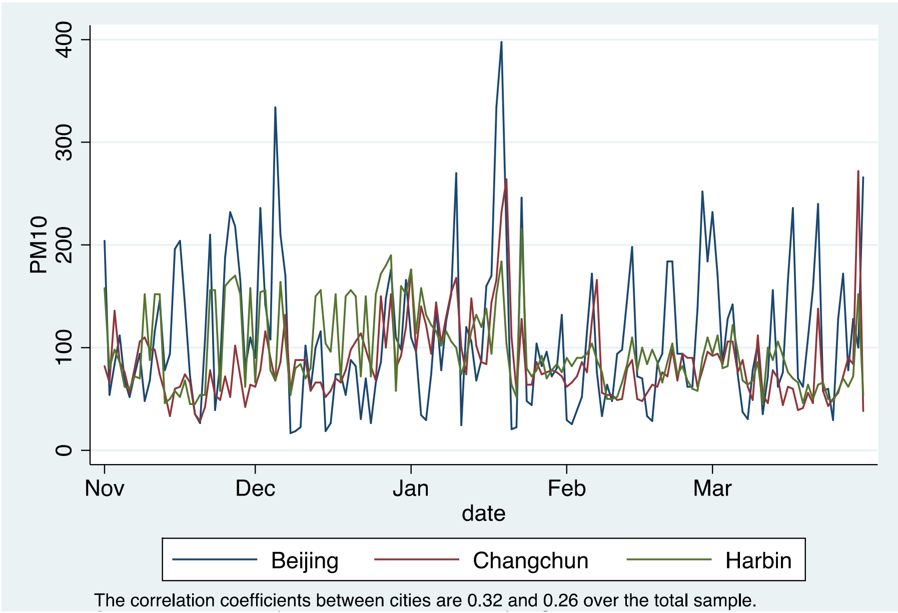
*Notes*: City-year-month fixed effects and dummy variables for weekends and national holidays are included in all model specifications. Robust standard errors are in parentheses, adjusted for spatial correlation, autocorrelation, and heteroscedasticity of the error terms. $N$=9,713.

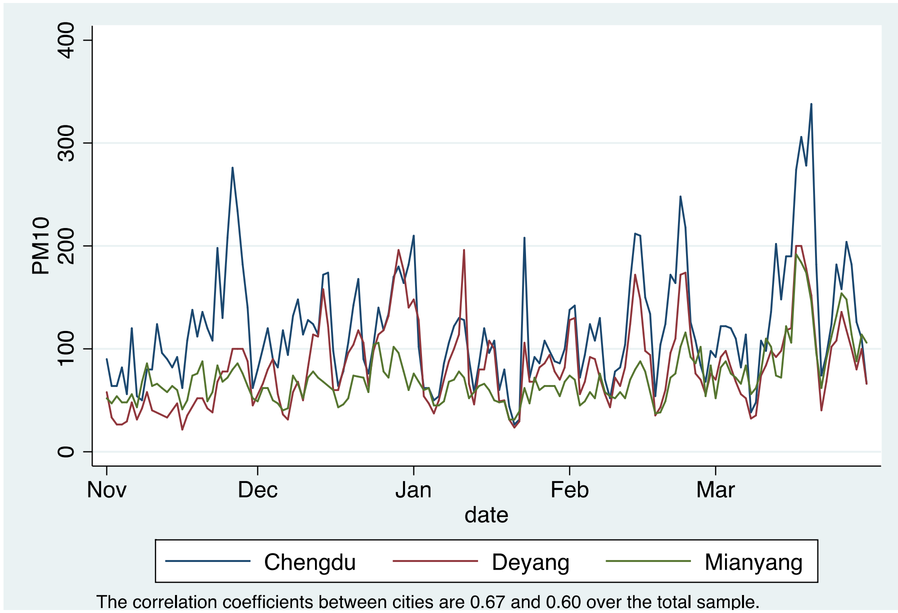
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$



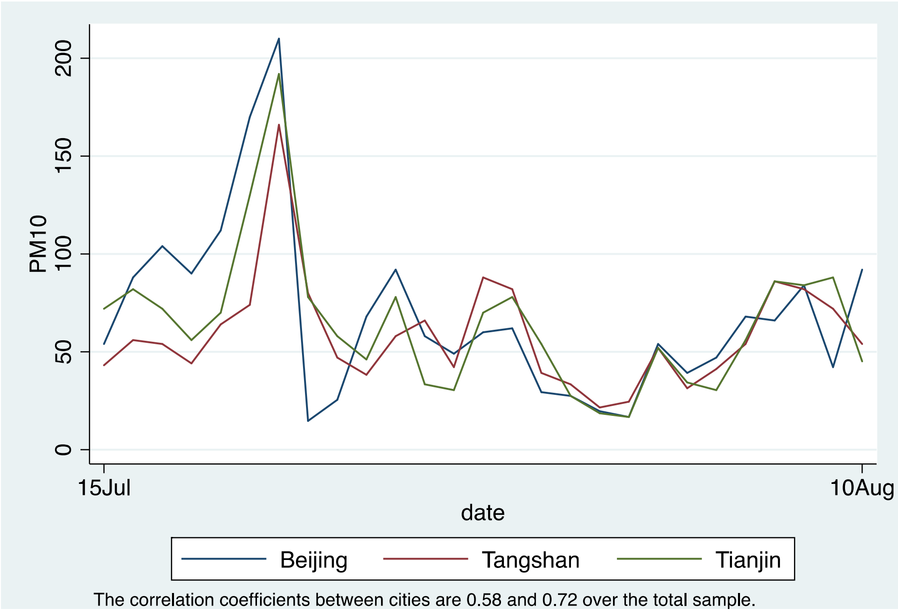

(a) Winter monsoon (b) Summer monsoon

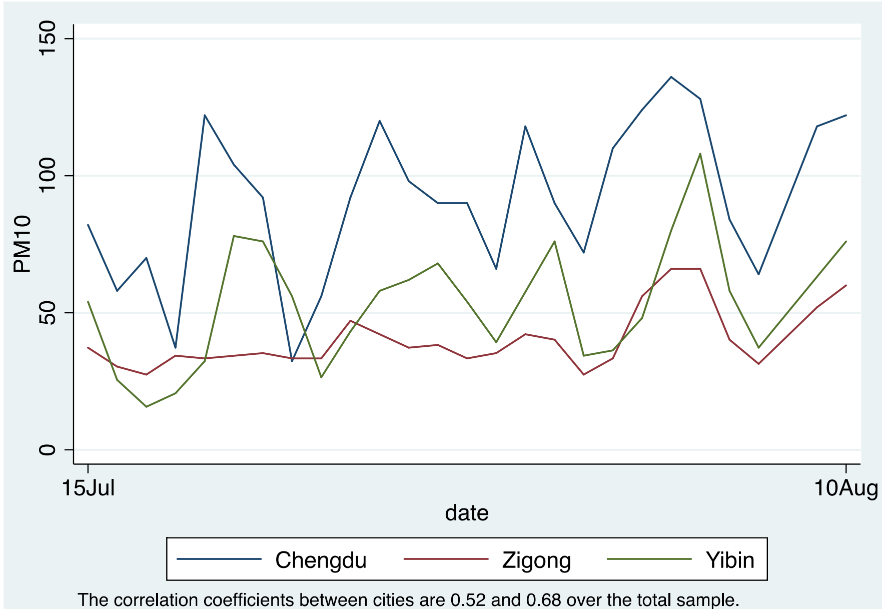
**Figure 1**. City-average $PM_{10}$ concentrations during the winter (a) and summer (b) monsoon seasons, 2009-2013




(a) Winter monsoon




(b) Summer monsoon

**Figure 2**. Spatial correlations of $PM_{10}$ concentrations in Chinese cities during the winter (a) and summer (b) monsoon seasons

*Notes*: Figure 2 is based on the 2012 data for Beijing and Chengdu.

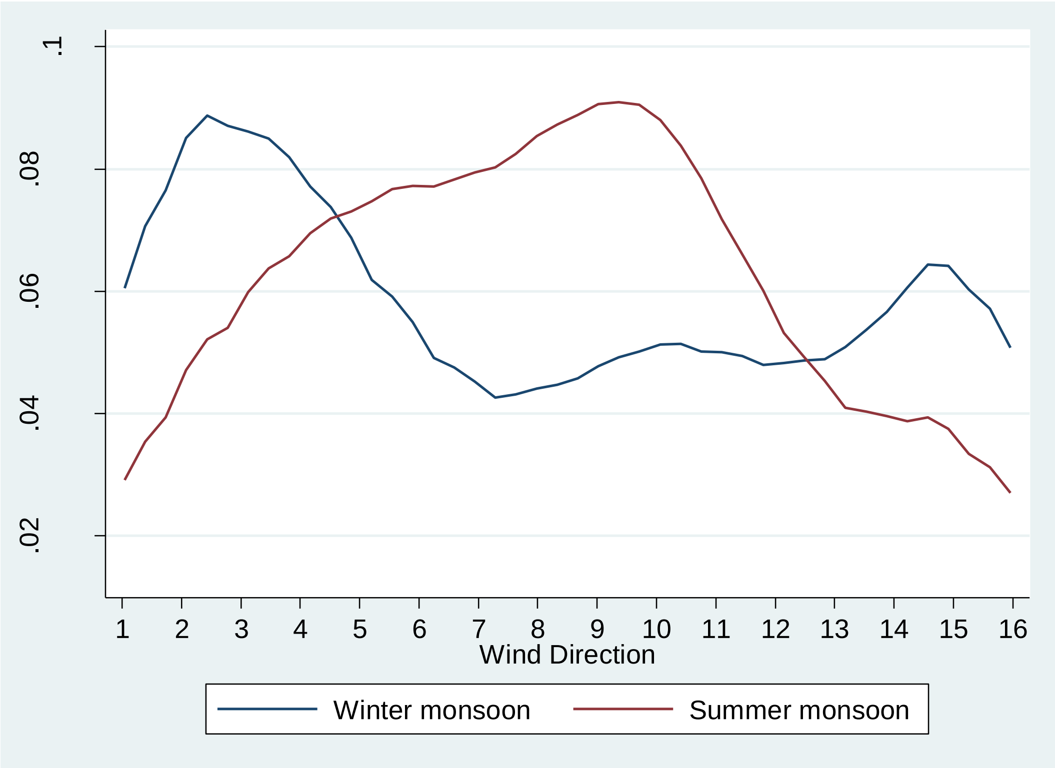
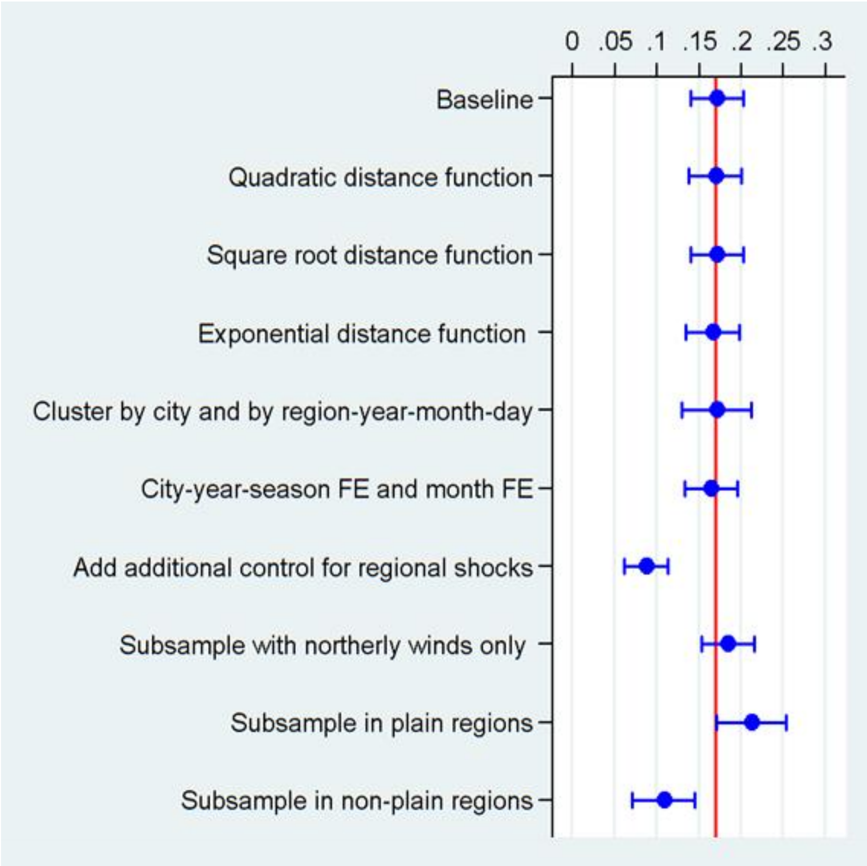
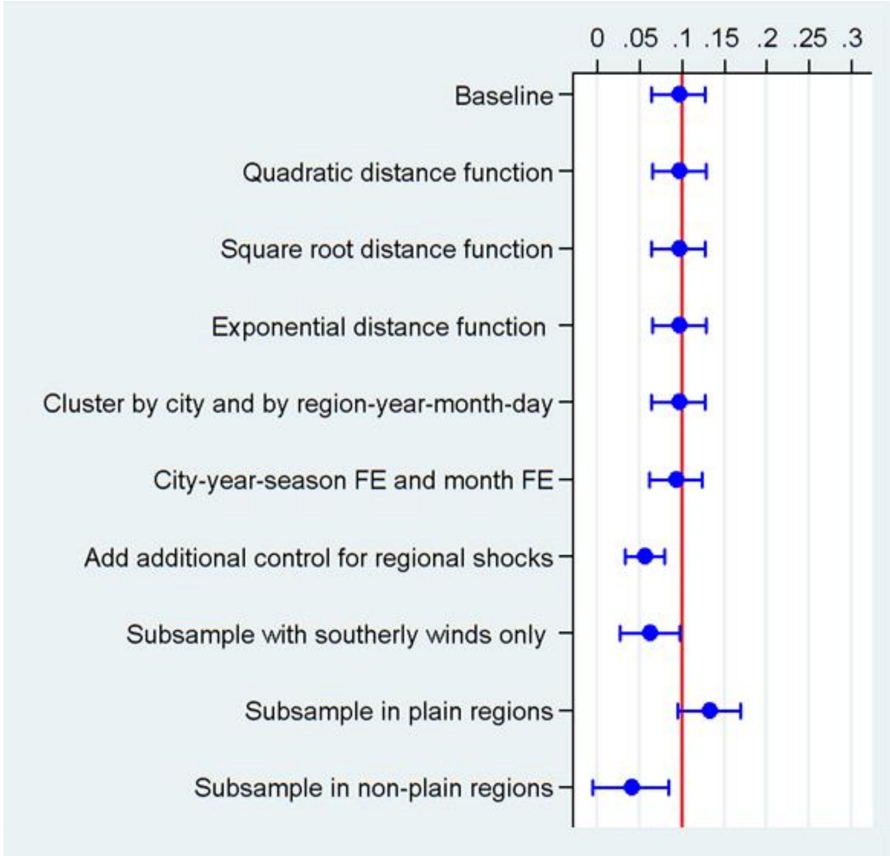



**Figure 3**. Wind direction during the winter and summer monsoon seasons

*Notes*: Wind directions are characterized by 16 cardinal directions, with cardinals of 1-5 and 13-16 denoting northerly winds and cardinals of 6-12 denoting southerly winds.



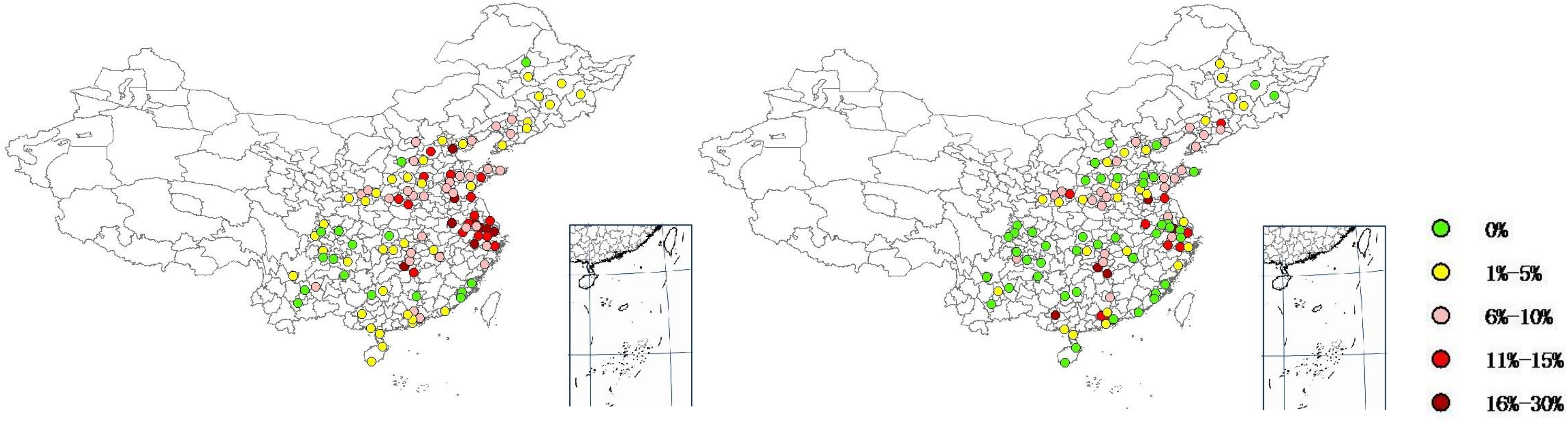

(a) Winter monsoon




(b) Summer monsoon

**Figure 4**. Sensitivity analysis

*Notes*: This figure shows the sums of coefficient estimates of the spatially-lagged $PM_{10}$ and the spatially and temporally-lagged $PM_{10}$ variables in different scenarios and their 95% confidence intervals.




(a) Winter monsoon (b) Summer monsoon

**Figure 5**. Percentage contributions of $PM_{10}$ from upwind cities to local $PM_{10}$ concentrations during the winter (a) and summer (b) monsoon seasons