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

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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 changes in wind direction can be fairly frequent. To circumvent these empirical challenges, we exploit spatial and temporal variations in PM10 concentrations for 108 major cities in China's Eastern Monsoon Region during the East Asian winter and summer monsoon seasons. We find large pollution spillover effects: a city's average PM10 concentration increases by 0.09-0.21 units during the winter monsoon season and by 0.06-0.10 units during the summer monsoon season, if PM10 concentrations in cities upwind of this city increase by one unit. The percentage contributions of PM10 pollution from upwind cities to local PM10 levels vary by region and can be as large as 30%. These findings are comparable to the existing atmospheric evidence. Our findings suggest that pollution control policies must be coordinated between cities to abate urban air pollution.

Acknowledgment:

JEL Codes: Q58, Q52

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ABSTRACT

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Keywords: Air pollution spillovers; PM₁₀; Wind; Monsoon; China

JEL classification: Q53, Q58

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 to set the stage for our study. These can be divided into two main categories, starting with the air sampling approach that entails measuring the content of particulate and gaseous contaminants in collected air samples. By analyzing ambient gases and aerosol properties in air samples, 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 sensitive to sampling sites, duration of sampling periods and sampling methods (Katz, 1969).³

The Air Quality (AQ) models are another widely-used approach, which utilizes 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. However, several studies have pointed out that simulation results based on the AQ models are sensitive to grid resolutions (see Queen and Zhang, 2008), and running these AQ models involves substantial computational costs (Capaldo et al., 2000).

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 Using the 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 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.

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, with a particular focus on estimating pollution spillovers effect. 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, this 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, 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 makes separating pollution spillovers from locally generated pollution difficult. Two, our data show frequent spatial and temporal changes in wind direction, making it even more difficult than in other contexts⁴ 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 major cities located in the Eastern Monsoon Region (EMR) in China⁵ 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 these major cities in the EMR during the two monsoon seasons,

⁴ Such as transboundary water pollution spillovers (Sigman, 2002).

⁵ 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).

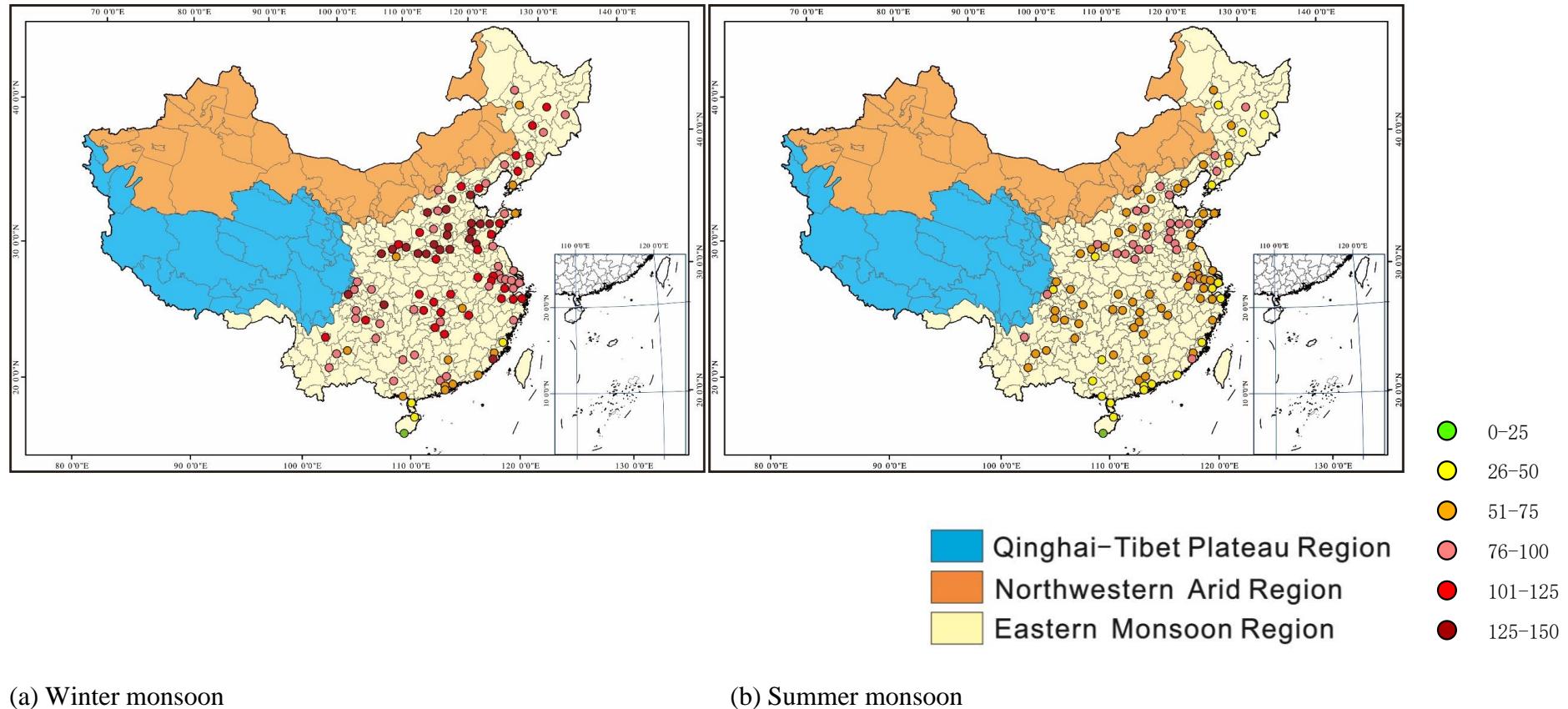


Figure 1. City-average PM₁₀ concentrations during the winter (a) and summer (b) monsoon seasons, 2009-2013

we can obtain clean estimates of pollution spillover effects. This identification strategy is similar to that used by Jia and Ku (2016) who assess the impacts of air pollution spillover from China to South Korea.

We conduct this analysis by compiling a 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.

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. We also 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 regional economic shocks, seasonal coal combustion for heat and power generation, dust generated 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 ranging from 0% to 30% during the winter monsoon season and from 0% to 26% during the summer monsoon

season, 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 three 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, we provide a new way to construct an instrumental variable for air quality. Chay and Greenstone (2005) used nonattainment status as the instrumental variable for air

quality to examine the impacts of air pollution on housing values.⁶ Luechinger (2009) improved their approach and used the changes in SO₂ concentration due to the mandated installation of SO₂ emissions control equipment in upwind areas as an instrument for SO₂ pollution. Here, we demonstrate that air pollution from areas upwind of a city can serve as a valid instrumental variable for that city's air quality, because air pollution levels are 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). Our empirical findings suggest that adjacent cities should establish environmental agreements to collectively control transboundary air pollution (Espínola-Arredondo and Muñoz-García, 2012).

The rest of the paper is organized as follows. Section 2 illustrates various factors that may affect urban PM₁₀ concentrations in China. Section 3 presents our empirical model. Section 4 describes data sources. Section 5 presents baseline results. Section 6 considers a variety of robustness checks. Section 7 assesses the percentage contributions of PM₁₀ pollution from upwind cities. Section 8 concludes.

2. Contributing factors to PM₁₀ pollution in Chinese cities

Based on their origins, we categorize the factors affecting a city's PM₁₀ 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 PM₁₀ transported from upwind regions by the passage of wind. In this section, we discuss each of these factors.

2.1 Local factors

Weather conditions, such as precipitation, wind, temperature, sunshine, relative humidity, and atmospheric pressure, have been well recognized as important factors affecting

⁶ 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.

ambient PM₁₀ 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 PM₁₀ concentrations. While wind affects the horizontal movement of PM₁₀, the literature on atmospheric pollution suggests that temperature influences the vertical movement of PM₁₀ (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 PM₁₀ away from the ground level, and reduce ground-level PM₁₀ concentrations. Other weather variables, such as sunshine hours, relative humidity, and atmospheric pressure, are also important factors affecting local PM₁₀ concentrations (Arya, 1999; Pankow et al., 1993).

The primary source of PM₁₀ 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, 2013). 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.⁷ 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 PM₁₀. Massive infrastructure construction in China in the past decade has generated a significant amount of dust.⁸ Illicit 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

⁷ "China vehicle emissions control annual report," available at: http://transportpolicy.net/index.php?title=China:_Compliance_and_Enforcement

⁸ The Chinese-language version of the website is available at: <http://www.bjepb.gov.cn/bjepb/323474/331443/331937/333896/396191/index.html>

and improve air quality, although the impacts of those policies are found to be mixed (Viard and Fu, 2015; Wang et al., 2014).

2.2 Neighboring factors

Because wind can transport certain air pollutants from one region to other regions, ambient PM₁₀ concentrations in areas downwind of a city are expected to be negatively affected by PM₁₀ 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 EPA also believes that international transport of air pollution has a significant negative impact on US air quality.⁹

3. Empirical methodology

3.1 Model specification

Following the above discussion, we estimate a regression model that accounts for both spatial and temporal correlations of PM₁₀ concentrations and considers a variety of local and neighboring factors that may affect urban PM₁₀ 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 PM₁₀ concentration for city i on day d in month m of year y , while $PM_{j,ymd}$ denotes the daily average PM₁₀ 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 PM₁₀ 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 PM₁₀ variable", and call $\sum_{j \neq i}^J \omega_{ij,ymd-1} PM_{j,ymd-1}$ "the spatially and temporally-lagged PM₁₀ variable". As noted above, we restrict our sample to observations of cities located in China's EMR during the East Asian monsoon seasons. Thus, PM₁₀ concentrations in city i may be affected by PM₁₀ pollution spilled over from upwind cities

⁹ "International transport of air pollution," available at: <http://www.millenniumbulkeiswa.gov/comments/MBTL-EIS-0002256-58930.pdf>

during a given monsoon season, but city i 's PM₁₀ concentrations are unlikely to influence PM₁₀ 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 PM₁₀ 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 PM₁₀ concentrations in a city exists only between day d and day $d-1$. τ captures this temporal dependency. Second, a city's PM₁₀ concentration on a given day is assumed to be affected by PM₁₀ pollution in cities upwind of this city on the same day and the previous day. ρ_1 and ρ_2 represent the spatial correlations of PM₁₀ concentrations. Our main hypothesis is to test whether $\rho_1 = \rho_2 = 0$, namely the null hypothesis that spatial spillover effects of PM₁₀ do not exist.¹⁰

$X_{i,ymd}$ includes weather, fuel prices, dummy variables for post-harvest seasons of crops, and dummy variables for weekends and national holidays. We consider a 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 PM₁₀ concentrations. An increase in gasoline price is expected to reduce vehicle miles traveled and thus total fuel consumption, which in turn may reduce urban PM₁₀ 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

¹⁰ We also considered adding spatially and temporally-lagged PM₁₀ 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.

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. β reflects the effects of these local factors on city-average PM_{10} concentrations.

3.2 Weighting scheme

To estimate ρ_1 and ρ_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 (Appendix A has detailed background on regional transport of PM). In light of this, we use three sources of information to specify our spatial weights matrices:

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

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 , $24 \text{ hours} < \frac{d_{i,j}}{ws_{j,ymd-1}} \leq 48 \text{ hours}$.

3.3 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,¹¹ 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) accounts for serial correlation within each city. We also allow for the heteroscedasticity of the error terms.

4. Data

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

¹¹ Another leading procedure estimating SDPD models is the (quasi) maximum likelihood estimation (MLE) (Lee and Yu, 2014).

4.1 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 .¹² 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”. Appendix B reports summary statistics of key variables.

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 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 100.¹³ 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 C1 in the Appendix C shows that PM_{10} concentrations between the two cities

¹² For a comprehensive discussion about the construction of API, see http://www.aqhi.gov.hk/pdf/related_websites/APIreview_report.pdf

¹³ 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.

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 ($p < 1\%$).

4.2 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 C2 in Appendix C 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).

4.3 Other control variables

We obtain gasoline prices from the National Development and Reform Commission (NDRC) for the sample period.¹⁴ The NDRC is the nation's top economic planner, and it sets baseline fuel prices in China. State-owned retailers are 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

¹⁴ See http://www.sdpc.gov.cn/zcfb/zcfbgg/index_2.html, last accessed on March 26, 2016.

mechanism implemented by the NDRC is still not fully market-driven (Zhang and Xie, 2016). We collect information on province-level post-harvest seasons of corn, wheat and rice from the Ministry of Agriculture of China.¹⁵ 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.

5. Baseline results

Tables 1 and 2 report the baseline results based on the observations during the winter monsoon season and during the summer monsoon season, respectively. In each table, we conduct the empirical analysis 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.

5.1 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.

¹⁵ The Chinese language version of the website is available at <http://202.127.42.157/moazzys/nongshi.aspx>, last accessed on March 26, 2016.

Table 1. Baseline results: Winter monsoon (dependent variable: PM₁₀ concentration)

| Variables | Model 1: Local factors only | Model 2: Add spatial PM ₁₀ | Model 3: Add lagged spatial PM ₁₀ |
|--|-----------------------------|---------------------------------------|--|
| Panel A: temporally- and spatially-lagged PM ₁₀ variables | | | |
| Temporally-lagged PM ₁₀ | 0.458*** (0.012) | 0.446*** (0.013) | 0.430*** (0.013) |
| Spatially-lagged PM ₁₀ | | 0.116*** (0.011) | 0.111*** (0.010) |
| Spatially and temporally-lagged PM ₁₀ | | | 0.061*** (0.009) |
| Panel B: Weather variables | | | |
| Precipitation | -0.103*** (0.016) | -0.101*** (0.015) | -0.101*** (0.015) |
| Sunshine duration | -0.172*** (0.021) | -0.159*** (0.020) | -0.158*** (0.020) |
| <i>T</i> _{max} | 0.278*** (0.018) | 0.271*** (0.018) | 0.278*** (0.017) |
| <i>T</i> _{min} | -0.135*** (0.022) | -0.135*** (0.022) | -0.141*** (0.022) |
| Average wind speed | -0.384*** (0.054) | -0.429*** (0.060) | -0.448*** (0.062) |
| Atmospheric pressure | -0.056*** (0.013) | -0.045*** (0.012) | -0.045*** (0.012) |
| Relative humidity | -0.022 (0.058) | 0.003 (0.055) | 0.019 (0.054) |
| Panel C: Economic variables | | | |
| Gasoline price | -0.005** (0.003) | -0.006** (0.003) | -0.006** (0.003) |
| Post-harvest season of rice | -0.287 (2.466) | -0.034 (2.392) | 0.377 (2.335) |
| <i>R</i> 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 2. Baseline results: Summer monsoon (dependent variable: PM₁₀ concentration)

| Variables | Model 1: Local factors only | Model 2: Add spatial PM ₁₀ | Model 3: Add lagged spatial PM ₁₀ |
|--|-----------------------------------|--|--|
| Panel A: temporally- and spatially-lagged PM ₁₀ variables | | | |
| Temporally-lagged PM ₁₀ | 0.321*** (0.020) | 0.315*** (0.020) | 0.313*** (0.019) |
| Spatially-lagged PM ₁₀ | | 0.082*** (0.013) | 0.082*** (0.013) |
| Spatially and temporally- lagged PM ₁₀ | | | 0.015 (0.011) |
| Panel B: Weather variables | | | |
| Precipitation | -0.011*** (0.002) | -0.012*** (0.002) | -0.012*** (0.002) |
| Sunshine duration | -0.143*** (0.022) | -0.137*** (0.022) | -0.136*** (0.022) |
| T_{\max} | 0.340*** (0.033) | 0.329*** (0.033) | 0.329*** (0.033) |
| T_{\min} | 0.025 (0.031) | 0.022 (0.031) | 0.022 (0.031) |
| Average wind speed | -0.257*** (0.043) | -0.265*** (0.044) | -0.267*** (0.044) |
| Atmospheric pressure | 0.017 (0.018) | 0.021 (0.018) | 0.022 (0.018) |
| Relative humidity | 0.139 (0.088) | 0.136 (0.087) | 0.136 (0.086) |
| Panel C: Economic variables | | | |
| Gasoline price | 0.004 (0.005) | 0.004 (0.005) | 0.003 (0.005) |
| Post-harvest season of rice | -1.483 (1.627) | -1.340 (1.564) | -1.340 (1.561) |
| Post-harvest season of corn | -2.354 (2.817) | -1.906 (2.709) | -1.777 (2.715) |
| Post-harvest season of wheat | 4.305 (2.706) | 4.695 (2.871) | 4.610 (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. $N=9,713$.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Spatial spillovers of PM₁₀ pollution

In Models 2 and 3, the coefficient estimates of “the spatially-lagged PM₁₀ 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).

5.3 Effects of weather on PM_{10} pollution

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_{min} is found to be negative and statistically significant ($p < 1\%$) for the winter monsoon sample, suggesting that higher T_{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_{min} has a positive sign but it is insignificant for the summer monsoon sample. The coefficient estimate of T_{max} is found to be positive and statistically significant ($p < 1\%$). While T_{min} typically occurs before sunrise, T_{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_{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).

5.4 Effects of economic variables on PM₁₀ pollution

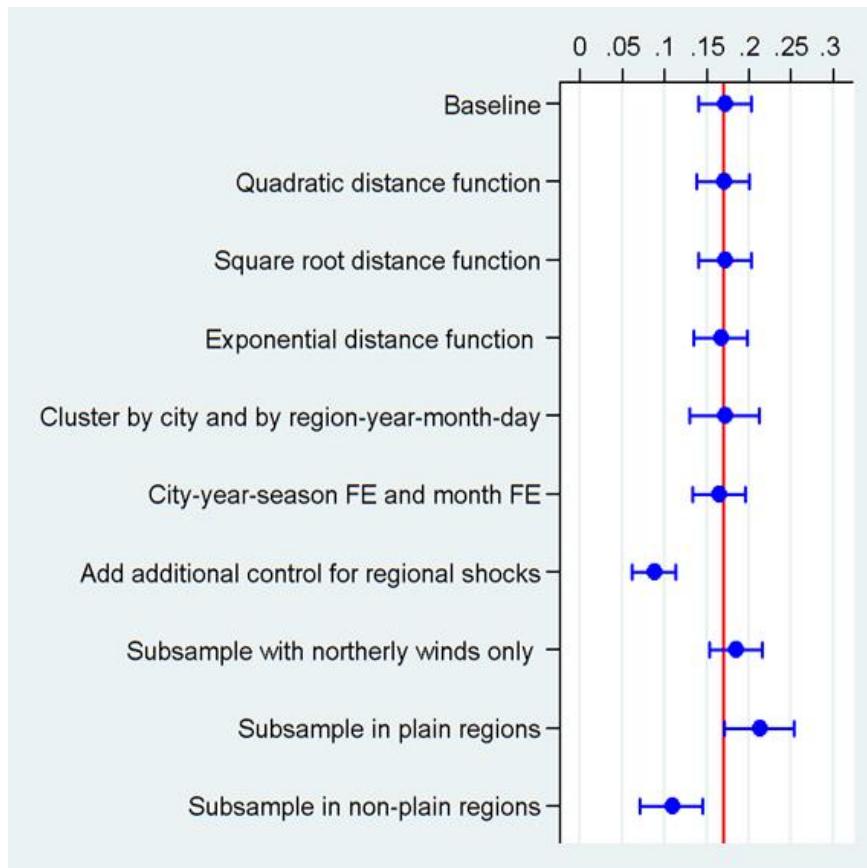
Parameter estimates of economic variables have expected signs and statistical significance. Coefficient estimates of the dummy variables for post-harvest seasons of rice, corn and wheat are insignificant, possibly because post-harvest seasons of the three crops are collected at provincial scale and the city-year-month fixed effects may have absorbed some of the effects of burning residues on PM₁₀ concentrations.

The coefficient estimate of gasoline price is negative and statistically significant for the winter monsoon sample, suggesting that increased gasoline prices have effectively improved air quality during the winter months, possibly by reducing fuel consumption. 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).

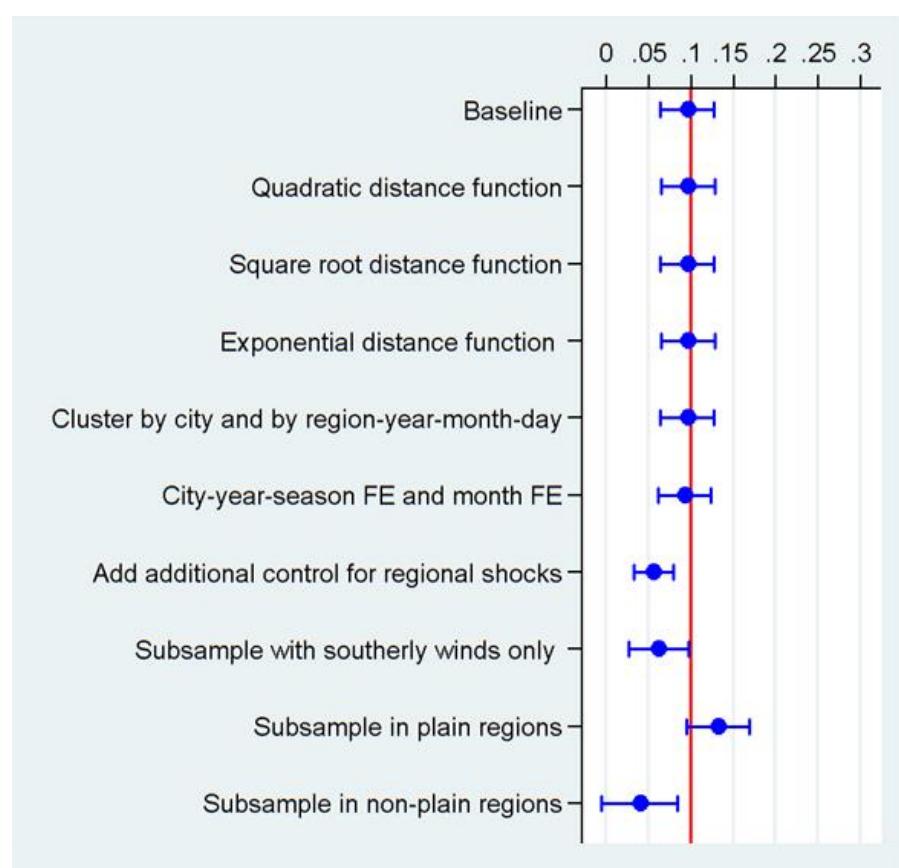
6. Robustness checks

The results presented above regarding the impacts of various factors on ambient PM₁₀ 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 PM₁₀ variable” and “the spatially and temporally-lagged PM₁₀ variable) and their 95% confidence bands across various scenarios in Figure 2.¹⁶

¹⁶ 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.



(a) Winter monsoon



(b) Summer monsoon

Figure 2. Sensitivity analysis

Notes: This figure shows the sums of coefficient estimates of the spatially-lagged PM₁₀ and the spatially and temporally-lagged PM₁₀ variables in different scenarios and their 95% confidence intervals.

6.1 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 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. 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 PM₁₀ 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. 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.

6.2 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 PM₁₀ 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. Figure 2 shows 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 C2). 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.

6.3 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 estimates¹⁷.

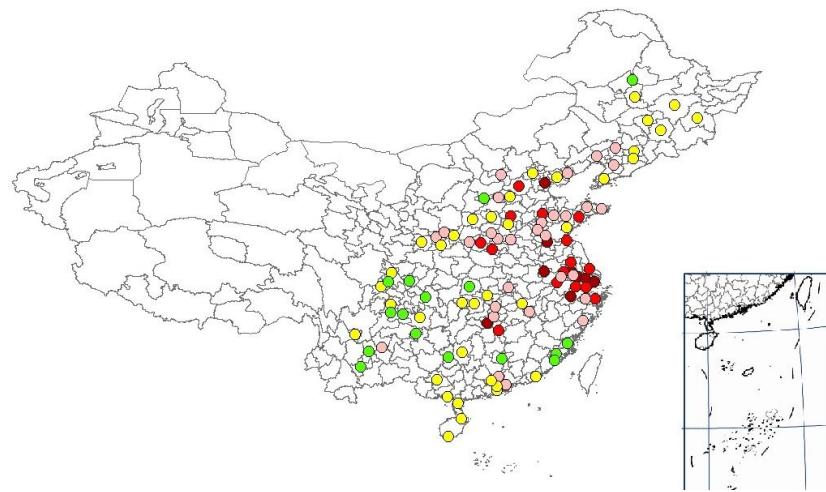
7. Assessment of the upwind impacts

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 ρ_1 and ρ_2 . We then compute θ_i for city i :

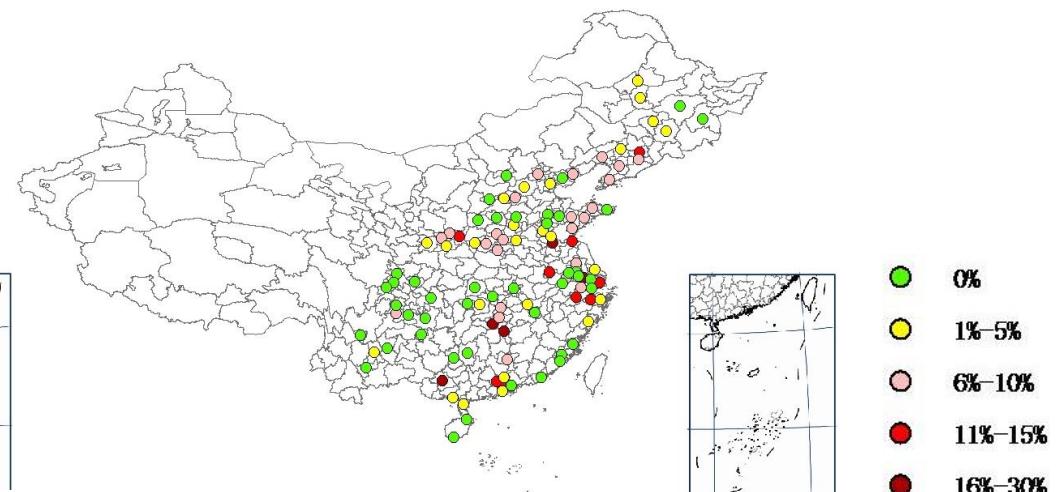
$$\theta_i = \frac{\sum_{j \neq i}^J E(PM_j)}{E(PM_i)} \quad (3)$$

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 ρ_1 and ρ_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, θ_i measures the “average” contribution of PM_{10} transported from upwind cities to city i ’s PM_{10} concentrations.

¹⁷ The estimated spillover effect in non-plain regions during the summer monsoon season is statistically insignificant.



(a) Winter monsoon



(b) Summer monsoon

Figure 3. Percentage contributions of PM₁₀ from upwind cities to local PM₁₀ concentrations during the winter (a) and summer (b) monsoon seasons

Figure 3 shows that there exist large variations in estimated θ_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 PM₁₀ 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 PM₁₀ 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 PM₁₀ 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 PM₁₀ levels relative to cities in northern China (see Figure 1).

8. Conclusions and discussion

In this paper, we exploit spatial and temporal variations in PM₁₀ 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 PM₁₀ concentrations in Chinese cities. To fully incorporate the spatial and temporal dynamics of PM₁₀ 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 PM₁₀ 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 PM₁₀ levels vary across regions, with cities located in the North China Plain and Yangtze River Delta regions most affected by pollution from upwind cities. Although our approach is different from the atmospheric approaches, these findings are fairly comparable to the existing atmospheric evidence.

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 PM₁₀ data used in the sample are not continuous, we may have underestimated the true spatial spillover effects of PM₁₀. Second, our sample includes only 108 major Chinese cities in the EMR. While we investigate the spatial correlations of PM₁₀ among these major cities, there are many small and medium-size cities located between these major cities. PM₁₀ 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 PM₁₀. On the cost side, there are a number of options to reduce PM₁₀ 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 PM₁₀ concentrations will change when emission levels change. On the benefit side, it is difficult to estimate the benefits stemming from reduced PM₁₀ concentrations, because the benefits depend not only on reduced PM₁₀ concentrations, but also on initial PM₁₀ levels. Moreover, estimating the benefits due to reduced PM₁₀ 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 PM₁₀ concentrations by one unit, average PM₁₀ 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:

Andrews, S.Q., 2008. Inconsistencies in air quality metrics: “Blue Sky” days and PM₁₀ concentrations in Beijing. *Environ. Res. Lett.* 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. *Resour. Energy Econ.* 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. *J. Bus. Econ. Stat.* 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. *Atmos. Environ.* 34, 3617–3627. doi:10.1016/S1352-2310(00)00092-3

Chakravorty, U., Umetsu, C., 2003. Basinwide water management: a spatial model. *J. Environ. Econ. Manage.* 45, 1–23. doi:10.1016/S0095-0696(02)00012-8

Chan, C.K., Yao, X., 2008. Air pollution in mega cities in China. *Atmos. Environ.* 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. *J. Polit. Econ.* 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. *Atmos. Environ.* 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. *Proc. Natl. Acad. Sci.* 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. *J. Environ. Econ. Manage.* 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). *Atmos. Environ.* 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. *Transp. Res. Part A Policy Pract.* 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. *Natl. Bur. Econ. Res. Work. Pap.* Ser. 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* (80-). 209, 1522–1524.

Ermak, D.L., 1977. An analytical model for air pollutant transport and deposition from a point source. *Atmos. Environ.* 11, 231–237. doi:10.1016/0004-6981(77)90140-8

Espínola-Arredondo, A., Muñoz-García, F., 2012. When do firms support environmental agreements? *J. Regul. Econ.* 41, 380–401. doi:10.1007/s11149-011-9170-3

Ghanem, D., Zhang, J., 2014. “Effortless Perfection:” Do Chinese cities manipulate air pollution data? *J. Environ. Econ. Manage.* 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. *J. Econ. Dyn. 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. *Am. J. Agric. Econ.* 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. *Proc. Natl. Acad. Sci. U. S. A.* 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. *Proc. Natl. Acad. Sci. U. S. A.* 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. *Geophys. Res. Lett.* 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. *J. Geophys. Res. Atmos.* 105, 1585–1597. doi:10.1029/1999JD900999

Katz, M., 1969. Measurement of air pollutants: Guide to selection of methods. World Health Organization, Geneva.

Kuwayama, Y., Brozović, N., 2013. The regulation of a spatially heterogeneous externality: Tradable groundwater permits to protect streams. *J. Environ. Econ. Manage.* 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. *J. Econom.* 180, 174–197. doi:<http://dx.doi.org/10.1016/j.jeconom.2014.03.003>

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. *Proc. Natl. Acad. Sci.* . doi:10.1073/pnas.1604537113

Luechinger, S., 2009. Valuing Air Quality Using the Life Satisfaction Approach*. *Econ. J.* 119, 482–515. doi:10.1111/j.1468-0297.2008.02241.x

Mayer, H., 1999. Air pollution in cities. *Atmos. Environ.* 33, 4029–4037. doi:10.1016/S1352-2310(99)00144-2

NBS, 2013. China Statistical Database.

Nickell, S., 1981. Biases in Dynamic Models with Fixed Effects. *Econometrica* 49, 1417–1426. doi:10.2307/1911408

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. *Environ. Sci. Technol.* 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* (80-). 220, 195–197.

Pfeiffer, L., Lin, C.-Y.C., 2012. Groundwater pumping and spatial externalities in agriculture. *J. Environ. Econ. Manage.* 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. *Atmos. Environ.* 42, 3856–3868. doi:10.1016/j.atmosenv.2007.12.066

Roodman, D., 2009. How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata J.* 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? *Am. Econ. Rev.* 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. *Atmos. Environ.* 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. *J. Geophys. Res.* 87, 8870. doi:10.1029/JC087iC11p08870

Viard, V.B., Fu, S., 2015. The effect of Beijing's driving restrictions on pollution and economic activity. *J. Public Econ.* 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. *Transp. Res. Part A Policy Pract.* 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. *Environ. Sci. Technol.* 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. *J. Environ. Econ. Manage.* 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 Econ. Rev.* 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. *Atmos. Chem. Phys.* 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. *Int. J. Climatol.* 31, 677–686.
doi:10.1002/joc.2101