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A Spatial Analysis of the Causal Factors Influencing China's Air Pollution

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ABSTRACT

This study investigates the factors that affect China's air pollution using city-level panel data and spatial econometric models. We address three air pollutants (PM_{10}, SO_2, and NO_2) present in 30 cities in China between 2004-2012 using global OLS and spatial models. To develop the spatial econometric analysis, we create a spatial weights matrix to define spatial patterns based on two neighborhood criteria—the queen contiguity and *k* nearest neighbors. The results show that the estimated coefficients are relatively consistent across different spatial weight criteria. The OLS models indicate that the effect of green spaces is statistically significant in decreasing the concentrations of all air pollutants. In the PM_{10} and SO_2 analyses, the OLS models find that the number of buses and population density are also positively related to a reduction in the concentration of air pollutants. In addition, an increase in the temperature and the presence of secondary industries increase SO_2 and NO_2 concentrations, respectively. All spatial models capture a positive and significant effect of green spaces on reducing the concentration of each air pollutant. Our results suggest that green spaces in cities should receive priority consideration in local planning aimed at sustainable development. Furthermore, policymakers need to be able to discern the differences among pollutants when establishing environmental policies.

Key words: Air pollution, China, City-level panel data, Green space, Spatial analysis

1. INTRODUCTION

Driven by the "reform and open-door" policy that was launched in 1978, China's economic growth has been remarkable in the last decades. Industrial development has led the exponential growth of China's GDP. From 1960 to 2015, China's urban population increased from 16% to 56%, and today more than 55% of the Chinese population lives in urban areas (Huang *et al*., 2016; World Bank, 2016; Wu *et al*., 2014). The rapid urbanization is a driver of the economic development of the country; however, urbanization and economic growth have resulted in environmental deterioration, with urban air pollution emerging as one of China's most pressing issues.

As a result of the domestic crisis and international pressure to reduce air pollution, the country has been trying to balance economic performance and environmental sustainability. For example, the Chinese government has issued environmental laws and regulations and called for the establishment of a national air pollution monitoring system, the implementation of research and development, and investment in environmental infrastructures (Xu *et al*., 2013; Zhang and Wen, 2008; He *et al*., 2002; He *et al*., 2001). It has also implemented various measures to prepare for the Beijing Olympic Games held in 2008 (Wang *et al*., 2009; Chan and Yao, 2008; Hao and Wang, 2005).

However, some scholars and policy makers have questioned the validity and effectiveness of China's environmental policies. China's megacities — Beijing, Shanghai, and Guangzhou — are still the world's most polluted cities (Chan and Yao, 2008; He *et al*., 2002). Particle Matter 10 (PM_{10}) has severely affected the capital city, Beijing, during 90% of the days between 1999 and 2005 (Chan and Yao, 2008). Millions of people in China are exposed to this environmental threat. Moreover, air pollution, as well as the PM_{10} and $PM_{2.5}$ originating from China, also affect Korea and Japan. In the attempt to find ways to effectively mitigate these issues, scholars have addressed the current state of air pollution in Chinese cities and its determinants (Wang and Hao, 2012; Wang *et al*., 2010; Chan and Yao, 2008; Shao *et al*., 2006; Hao and Wang, 2005; He *et al*., 2002). Previous studies indicate that urban air pollution is strongly related to economic development (Hao and Wang, 2005; He *et al.*, 2002). The main sources of China's air pollution are the growing coal consumption, motor vehicle use, and changes in urban land use, particularly the reduction in the size of urban green areas.

Most previous studies were limited by their focus on representative big cities, such as Beijing and Shanghai. However, to understand the reality and causes of air pollution in China, we need to apply an in-depth analysis to various cities with different economic and environmental conditions. As the Chinese government advocates the "New Normal" policy, which considers the balance between the environment and economic growth for the next stage of the country's economic development, effective ways to reduce pollution need to be investigated. To this end, addressing various cities with different economic and environmental background allows us to identify the factors that affect China's air pollution, and provides meaningful implications to achieve the so called "New Normal" in China.

Most previous studies regarded a city as an independent point in a random distribution. However, the information obtained from administrative units, such as cities or provinces, consists of geo-referenced data with spatial autocorrelation. Furthermore, most environmental pollution data are based on areas; however, traditional regression methods ignore the spatial dependency within data. For instance, the traditional ordinary least squares (OLS) model assumes independent and identically distributed error terms and may underestimate the parameters of interest in the presence of a significant spatial correlation within the data. Therefore, to accurately assess the influence of all the variables, the spatial factors need to be considered.

In particular, for a vast country such as China, spatial analysis is more suitable than traditional approaches since the natural environment, lifestyle, and industrial structure vary across regions. The factors affecting regional air pollution may be different across cities, and these effects may be underestimated by global estimation models that focus on the entire country. However, only a few studies consider the spatial characteristics of different regions in China to address the determinants of air pollution. In particular, only a few studies investigate the distribution or emission intensity of air pollutants and their determinants using a spatial approach (Tang *et al.*, 2016; Zhao *et al.*, 2014; Chen, 2013).

In this study, we adopted spatial econometric models to exploit the potential for data and methodological improvements in the estimation of the determinants of China's air pollution. We apply both global OLS fixed effects models and spatial fixed effects models to three air pollutants – PM_{10}, sulfur dioxide (SO_2), and nitrogen dioxide (NO_2) – present in 30 Chinese cities (Fig. 1)[1].

We use pollution data from 2004 to 2012 since the Chinese government has adopted a new standard air quality index in 2013 (GB3095-2012) to address the development problems of urbanization (Ministry of Environmental Protection of the People's Republic of China, 2016).

2. METHODOLOGY

This study addresses the determinants of air pollution in Chinese cities considering the spatial dependence among observations. To this end, we built a city-level panel dataset and estimated spatial econometric models.

The basic premise of spatial econometric models is positive spatial dependence, whereas conventional regression models assume that observations are independent of each other. This assumption implies the lack of spatial relationship between observations from nearby locations. However, if observations are collected based on spatial scales (i.e., countries, administrative regions, or postal districts), these observations tend to be spatially dependent. In other words, region-level observations from a certain location have values analogous to those from neighboring areas (Fischer and Getis, 2009). In this regard, a conventional regression model, such as a global OLS model, may not be the best framework to apply to regional data samples. Therefore, we adopt a spatial approach that allows us to consider the dependence among spatial units.

We consider a simple pooled linear regression model with spatial effects:

$$y_{it} = X_{it}\beta + \mu_i + \varepsilon_{it}, \quad (1)$$

where i represents cross-sectional spatial units and t represents the time of the observation. In addition, y_{it} is a dependent variable at location i in year t, and X_{it} is 1-by-k vector of independent variables; β denotes a matching k-by-1 vector of parameters that is fixed but unknown, and ε_{it} is the error term for location i in year t. When we consider the interaction effect between spatial observations, the model has a spatially lagged dependent variable and assumes that the observed dependent variables are affected by neighboring variables:

[1]The 30 cities are Anhui, Beijing, Fujian, Gansu, Guangdong, Guangxizhuangzu, Guizhou, Hainan, Hebei, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Jiangxi, Jilin, Liaoning, Neimenggu, Ningxiahuizu, Qinghai, Shaanxi, Shandong, Shanghai, Shanxi, Sichuan, Tianjin, Xinjiang, Xizang, Yunnan, and Zhejiang.

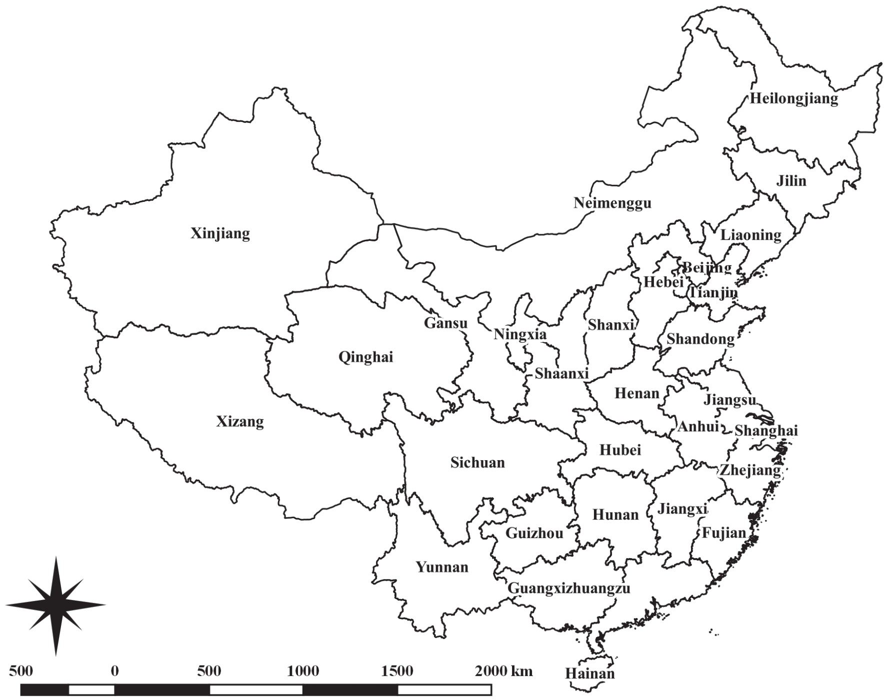

Fig. 1. 30 major cities in China used for the analyses in this study.

$$y_{it} = \delta \sum_{j=1}^{N} W_{ij} y_{jt} + X_{it}\beta + \mu_i + \varepsilon_{it}, \quad (2)$$

where δ is the spatial autoregressive coefficient; thus, if $\delta = 0$, the spatial panel model corresponds to a traditional panel model (Xiao *et al.*, 2014). W_{ij} is an n-by-n spatial weighted positive matrix that constrains the contiguity definition to determine whether a certain region is a neighbor to another region. In other words, this matrix represents the intensity of the relationship between cross-sectional units appearing in both rows and columns. Thus, contiguity relations that define the number of neighbors for region i can be selected based on the contiguity definition. There are various methodologies to define contiguity among spatial observations in matrix W; $W_{ij} = 1$ means that regions i and j are directly adjoining, and $W_{ij} = 0$ means that they are not (Xiao *et al.*, 2014; Millo and Piras, 2012; Fischer and Getis, 2009)[2].

This study adopts two neighborhood criteria – the queen contiguity and k nearest neighbor criterion – to assign weights to neighbors. The queen contiguity, like the queen piece in chess, regards polygons sharing boundary points as neighbors. Hence, matrix W contains 0 for regions that are not adjoined to region i, and values $1/n$ for the n neighboring regions of region i. The k-nearest neighbor criterion calculates the distance between neighbors. Figs 2 and 3 show the relationships between polygons for the criteria of queen contiguity and three nearest neighbors, respectively, in

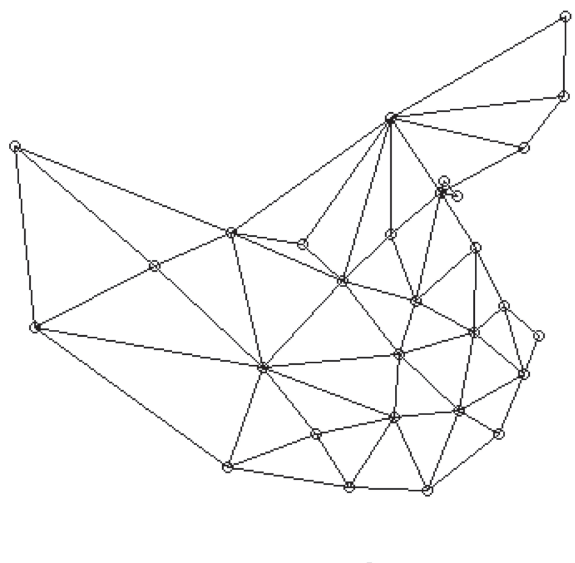

Fig. 2. Relationships between polygons for the queen contiguity criterion in the 30 Chinese cities under analysis.

[2]It is often believed that the influence of matrix W on the estimated results is considerable. Some scholars, such as LeSage and Pace (2009), however, disagree (Fischer and Getis, 2009).

the 30 cities analyzed in this study.

To develop a spatial econometric model, we create a spatial weights matrix to define the patterns in China's panel dataset. This study utilizes fixed-effects for the maximum likelihood estimation of spatial panel models. The model reads as follows:

$$Pollutants_{it} = \beta_0 + \beta_1\, GRESP_{it} + \beta_2\, BUS_{it} + \beta_3\, RAIN_{it} + \beta_4\, TEMP_{it} + \beta_5\, POPDEN_{it} + \beta_6\, INDUS_{it} + \varepsilon_{it}, \quad (3)$$

where $Pollutants_{it}$ is the concentration of the air pollutant ($\mu g/m^3$)[3] for PM_{10}, SO_2, or NO_2 in province i in year t. β are the parameters to be estimated, *GRESP* is the proportion of green space in each urban area (%), and *BUS* denotes the number of buses per person (veh/person). We consider two environmental factors, *RAIN* and *TEMP*, which indicate precipitation (mm) and temperature (ºC) in each city, respectively. Population density is also included as a variable, *POPDEN* (persons/m^2). *INDUS* is the ratio of secondary industries (resource extraction industries) to provincial gross regional product (GRP), and ε_{it} is the error term.

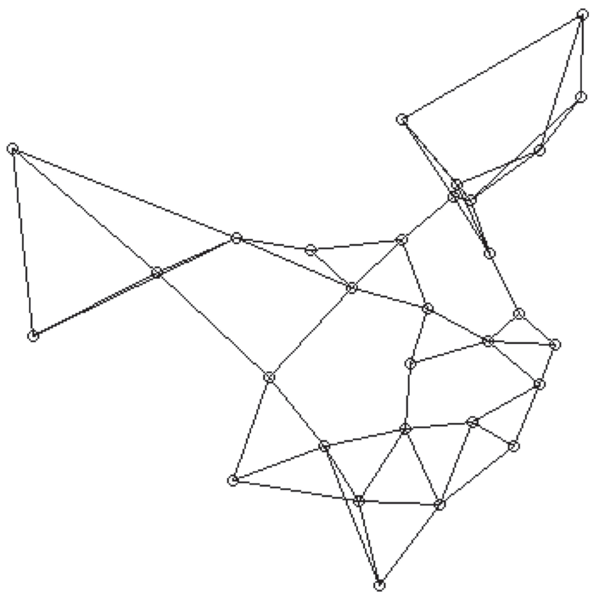

Fig. 3. Relationships between polygons for the three nearest neighbors criterion in the 30 Chinese cities under analysis.

We build three spatial panel datasets including information from 30 cities in China observed for nine years, from 2004 to 2012, for each pollutant – PM_{10}, SO_2, or NO_2. Regarding the dependent variables, we adopt the Air Pollution Index (API), which reports the concentrations of each air pollutant, from the China Statistical Yearbooks on Environment (National Bureau of Statistics of China, 2005-2014a). The independent variables that are expected to affect air pollution in China are collected from the China Statistical Yearbooks, the China City Statistical Yearbooks (National Bureau of Statistics of China, 2003-2015, 2005-2014b), and the China Agriculture Yearbooks (Editorial Board of China Agriculture Yearbook, 2005-2013). Table 1 shows the descriptive statistics and information for each variable used in this study. We employ the "splm" package in R, version 3.2.4 (Millo and Piras, 2012; Bivand *et al*., 2008) for the analysis.

3. RESULTS AND DISCUSSION

Tables 2, 3, and 4 report the estimation results of the global OLS models and the spatial weight models for each pollutant, PM_{10}, SO_2, and NO_2, respectively. The coefficients in the OLS models indicate larger impacts than in the spatial models. The results of the spatial weight models show that fewer factors influence air pollutants if spatial characteristics are considered. The estimated coefficients are relatively consistent across the two spatial weight criteria, queen contiguity and k nearest neighbors.

As shown in the first column of Tables 2 and 3, the

Table 1. Descriptive statistics of variables.

Variable	Definition	Unit	Mean	St. dev.	Min.	Max.
PM_{10}	PM_{10} Concentration	$\mu g/m^3$	102.127	31.343	33.000	305.000
SO_2	SO_2 Concentration	$\mu g/m^3$	45.703	20.976	3.000	116.000
NO_2	NO_2 Concentration	$\mu g/m^3$	41.367	13.140	12.000	73.000
GRESP	Ratio of green space in urban area	%	2.240	4.093	0.052	19.605
BUS	Number of buses per person	veh./person	0.077	0.037	0.017	0.214
RAIN	Precipitation in major cities	mm	855.397	503.718	74.900	2628.200
TEMP	Temperature in major cities	ºC	14.147	5.056	4.300	25.400
POPDEN	Population density	persons/m^2	0.593	0.419	0.015	2.259
INDUS	Ratio of secondary industry to GRP	%	44.570	7.944	22.320	60.130

[3]The unit "μg" is an abbreviation of microgram, which means one millionth (1/1,000,000) gram.

Table 2. Result: PM_{10}.

Variable	OLS model		Spatial model			
			Queen contiguity		k nearest neighbor (k=3)	
	Coefficients	Std. error	Coefficients	Std. error	Coefficients	Std. error
GRESP	−1.111·	0.596	−0.760	0.506	−0.812·	0.491
BUS	−248.030***	56.469	−129.660*	51.054	−129.550*	51.331
RAIN	−0.001	0.004	0.000	0.003	0.001	0.003
TEMP	1.340	1.197	0.520	1.204	−0.303	1.169
POPDEN	−35.486*	16.730	23.196	15.226	23.642	14.913
INDUS	0.266	0.288	0.375	0.251	0.379	0.238
rho	–	–	0.491***	0.064	0.486***	0.059
N	270		270		270	
Adjusted R^2	0.136		–		–	

Note: '·', '*', '**', and '***' represent the 10%, 5%, 1% and 0.1% significance levels, respectively.

Table 3. Result: SO_2.

Variable	OLS model		Spatial model			
			Queen contiguity		k nearest neighbor (k=3)	
	Coefficients	Std. error	Coefficients	Std. error	Coefficients	Std. error
GRESP	−2.054***	0.508	−1.112**	0.405	−1.517***	0.427
BUS	−123.083*	48.092	−14.474	40.971	0.297	44.057
RAIN	−0.003	0.003	−0.004	0.003	−0.003	0.003
TEMP	2.392*	1.019	2.304*	0.977	2.503*	0.997
POPDEN	−47.245**	14.248	−26.056*	12.237	−19.916	12.851
INDUS	−0.065	0.245	0.046	0.200	0.034	0.208
rho	–	–	0.546***	0.060	0.415***	0.064
N	270		270		270	
Adjusted R^2	0.184		–		–	

Note: '·', '*', '**', and '***' represent the 10%, 5%, 1% and 0.1% significance levels, respectively.

Table 4. Result: NO_2.

Variable	OLS model		Spatial model			
			Queen contiguity		k nearest neighbor (k=3)	
	Coefficients	Std. error	Coefficients	Std. error	Coefficients	Std. error
GRESP	−0.428·	0.243	−0.405·	0.225	−0.420·	0.225
BUS	10.996	22.982	9.705	21.658	9.607	21.592
RAIN	0.000	0.001	0.001	0.001	0.000	0.001
TEMP	0.544	0.487	0.450	0.471	0.505	0.463
POPDEN	0.609	6.809	−1.595	6.420	−0.140	6.387
INDUS	0.397***	0.117	0.401***	0.110	0.398***	0.109
rho	–	–	0.107	0.085	0.063	0.080
N	270		270		270	
Adjusted R^2	0.075		–		–	

Note: '·', '*', '**', and '***' represent the 10%, 5%, 1% and 0.1% significance levels, respectively.

non-spatial estimation of PM_{10} and SO_2 concentrations deliver similar results. The OLS results in Table 2 indicate that green spaces, the number of buses, and population density have statistically positive and significant effects on reducing PM_{10} concentrations in the Chinese cities under analysis. The OLS results for SO_2 concentrations (Table 3) show that green spaces, the number of buses, and population density are the factors that mitigate SO_2 concentrations in cities, in line with the results for PM_{10} concentrations.

The values of the spatial autocorrelation coefficient (*rho*) indicate significant and positive spatial autocorrelation only in the PM_{10} and SO_2 analyses. These results suggest that a city located near other highly polluted cities is expected to have higher levels of PM_{10} and SO_2. Furthermore, a comparison between the significant results in the OLS model estimation and the (lack of) significant results in the spatial model estimation — for example, the estimates on *BUS* for both PM_{10} and SO_2 — indicates a possible overestimation of the effects of green spaces on PM_{10} concentrations when we introduce spatial effects in the analysis.

The results of the spatial models for PM_{10} concentrations indicate that the number of buses and green spaces significantly reduce PM_{10} concentrations, and the results for SO_2 suggest that green spaces have a positive effect on reducing SO_2 concentrations, in line with the findings of the OLS analysis. Furthermore, cities with high population density tend to have lower SO_2 concentrations according to the spatial models based on queen contiguity, whereas the number of buses does not seem to be a significant factor in reducing pollutant concentrations. Temperature is a significant factor in increasing SO_2 concentrations according to the results of both non-spatial and spatial model estimations.

Our estimation results on population density and temperature are in line with the regional characteristics of China. Stationary emission sources generate SO_2 concentrations. In particular, in China, many power plants are still using coal for generating electricity. Most power plants are located on the outskirts of a city, in line with the Urban and Regional Planning. Regarding the influence of temperature on SO_2 concentrations, the leading regions for industry development are concentrated in the north-eastern part of the country due to imbalanced regional development, while the annual temperature in the South of China is higher than in the north-eastern region. The estimation results show a negative and positive coefficient on population density and temperature, respectively.

The results for NO_2 concentrations are reported in Table 4 and show that the statistically significant coefficients are consistent in all the three models, both in the non-spatial and spatial estimations. Interestingly, the *rho* coefficient is not significant in the NO_2-concentration model. We find no significant effects related to spatial autocorrelation in NO_2 concentrations among Chinese cities. This suggests that NO_2 concentrations have a low degree of spatial correlation in China in comparison with the concentrations of PM_{10} and SO_2. In all models, we observe that the ratio of green spaces in urban areas significantly contributes to decreasing NO_2 concentrations, alongside other pollutants. In contrast, the ratio of secondary industry, which represents the development of the manufacturing sector in cities, has a significant impact on NO_2 concentrations in China. However, since this study focused on the use of public transportation, these results cannot be generalized to the whole transportation industry.

Our results provide several important implications for reducing air pollution in China. First, the results of our analysis highlight the importance of green spaces for reducing air pollutant concentrations, in line with the findings of previous studies (Makhelouf, 2009; Jim and Chen, 2008). Both non-spatial and spatial analyses for PM_{10}, SO_2, and NO_2 emissions (all model specifications) find a significant and positive effect of green spaces on reducing pollutant concentrations. This suggests that efforts to create and improve green spaces in cities may effectively improve air quality in Chinese towns. Hence, green spaces in cities should receive priority consideration in local planning aiming at sustainable development.

Second, the empirical evidence from spatial analysis shows that the determinants for each air pollutant are different and may be affected by spatial variations. However, most emission reduction strategies usually focus on general factors, such as reducing vehicle emissions (Wolff and Perry, 2010; Krzyzanowski *et al*., 2005), in line with previous studies, which identified vehicle emissions as the primary source of these emissions (Tiwari *et al*., 2012; Ostro *et al*., 2011; Holman, 1999). In this respect, this study suggests the importance of discerning among pollutants and regions when establishing environmental policies. Policy makers should consider regional characteristics and spatial variations among pollutants based on the empirical results, which revealed a significant spatial correlation among the variables of interest.

Finally, this study finds that different factors are related to the sources of PM_{10}, SO_2, and NO_2 concentrations in Chinese cities. The secondary industry ratio is a significant factor in increasing NO_2 concentrations, whereas public transportation mitigates PM_{10} concentrations. Thus, environmental policies controlling secondary industries, which include oil and gas extraction and mining, and encouraging citizens to use public transportation are likely to be effective in mitigating NO_2 and PM_{10} concentration, respectively.

4. CONCLUSION

To investigate the factors that affect China's air pollution, this study applies global OLS and spatial models to three air pollutants — PM_{10}, SO_2, and NO_2 — using a city-level panel dataset for 30 Chinese cities observed between 2004 and 2012. The empirical results provide important implications for mitigating air pollution in Chinese cities. All the spatial models applied in this study show a positive and significant effect of green spaces on reducing pollutant concentrations. The results indicate that the impact of green spaces is significant in reducing the concentration of all pollutants considered in this study; thus, efforts to create and improve urban green spaces will significantly contribute to improve air quality in Chinese towns. Moreover, environmental policies should consider spatial variations: this study finds a significant and positive spatial autocorrelation in the spatial models of PM_{10} and SO_2. Different determinants for each air pollutant have a major impact on the effective reduction of air pollution.

Even though this study can offer meaningful insights into how to achieve a balanced economic growth in various regions, it suffers some limitations. We address only a small number of air pollutants – PM_{10}, SO_2, and NO_2 – observed for a limited period (nine years). Further empirical analyses are required to identify other factors affecting air pollution in China and the potential differences among air pollutants. We believe that further studies can investigate these aspects by improving the dataset. Studies focusing on other types of pollution, such as water pollution or industrial waste, would also be helpful to capture the current state of pollution and contribute to effective environmental policies.

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