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How does government attention matter in air pollution control? Evidence from government annual reports

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ABSTRACT

Ambitious environmental action demands policymakers' attention. Since 2014, when China proclaimed a "war on pollution," government attention to environmental concerns has increased unprecedentedly. The purpose of this study is to determine empirically if, and to what extent, this government attention has had an effect on environmental quality, particularly local air pollution. We quantified local Chinese governments' attention to the environment from 2014 to 2019 using a dataset of the textual content of their Government Annual Reports (GARs) from 286 cities at or above prefectural level (APL). The Spatial Durbin Model (SDM) is selected as the most probable spatial econometric model using Bayesian posterior model probabilities. As demonstrated, environmental attention is related with perceptible increases in air quality. On average, a one-unit increase in environmental attention resulted with decreases of 4.2 %, 4.5 %, and 7.4 % in AQI index, PM_{10}, and NO_2 concentrations, respectively. As an auxiliary validation, we found evidence at provincial level that environmental agenda and investment in pollution control represent the primary outputs of increased environmental attention. A further analysis by subsample revealed that the effect of environmental attention on air pollution differed by region. In general, this study establishes a compelling rationale for municipal governments to prioritize environmental issues and devote additional attention and resources to pollution control.

1. Introduction

The Chinese government has predominantly prioritized economic development over environmental pollution control for decades, resulting in a historical contradiction between a thriving economy and rising environmental degradation (Qi et al., 2008; Zhang et al., 2019; Zhang, 2021; Wang et al., 2021). This situation remained unchanged until the 18th National Congress of the Communist Party of China (CPC) convened in 2013, marking a watershed moment in China's history of environmental management and pollution. In 2014, China declared a "war on pollution" (Greenstone et al., 2021). The new *Environmental Protection Law*, as well as the *Action Plan for the Prevention and Control of Air Pollution*, were issued. Government attention has been increasingly focused on environmental challenges in recent years as a critical component of the policy-making process, signaling the government's policy objectives (Wang and Meng-Zhu, 2017). As a possible result, significant improvements in environmental quality, particularly local air pollution, are being perceived in a number of places throughout mainland China (Azimi et al., 2020). Our objective thus is to examine how local governments' attention to environmental degradation impacts the regional environment's quality from a government perspective.

Attention, as used here, was originally a psychological concept. In the late 20th century, Herbert A. Simon, the Nobel Prize winner in economics, put forward the concept of "attention". He believed that attention is "the process in which managers selectively pay attention to some information while ignoring other parts" (Simon, 1976). Due to time, effort, and cost constraints, decision-makers cannot handle multiple transactions at the same time. They thus need to determine which information and which transactions are important or urgent. This process of judgment is the process of attention distribution or diversion (Simon, 1976). Based on Simon's research on attention, American scholars Bryan D. Jones et al. (1993) introduced attention into the field of government decision-making and then proposed the "attention-driven policy choice model". Jones points out that all decisions involve

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selectivity. How to select what is relevant or of greatest concern is important to the decision-making process. This selective effect of attention led Jones to conclude that "as the attention of policymakers shifts, government policy also changes" (Jones and Baumgartner, 2005, 2012).

In different political systems, heads of government and decision-makers deliver their attention on public issues in different ways. In Britain, a "Speech from the Throne", the King's or the Queen's Speech, plays a vital role in providing general statements about executive priorities (John and Jennings, 2010). The Queen's Speech enables governments to set out their legislative plans and delineate their policy choices, through which policy preferences are articulated and justified by governments (Kelso, 2017). In the USA, the annual State of the Union address indicates the priorities of policy-makers in domains such as international affairs (Cohen, 1995). Numerous researchers have addressed how the notion of attention has altered government decision-making (Uiterkamp et al., 2011). Jones et al. (1993) show that poverty was a relatively minor public issue in the 1950s, but became a central public problem in the 1960s as governments shifted their focus toward this structural issue. More recently, Flavin and Franko (2017) analyzed the distribution of the government's attention to the political rights of citizens by using the bills and documents of American state legislatures. Balderas Torres et al. (2020) use the archived documents in presidential websites for publications to study the attention paid by Mexican presidents to climate change. And in the field of environment, the research about government attention is also rising rapidly (Wang et al., 2018; Hooper et al., 2018; Salvia et al., 2021; Peterson, 2021).

In China, Government Annual Reports (GARs) are extensive guidance papers akin to the Queen's Speech and the State of the Union address (Yang and Zheng, 2020), and have been used to analyze a variety of problems, including governments' attention allocation. GARs often outline a government's accomplishments during the last one or five years and set strategic objectives for the next one or five years based on certain factors such as GDP development, environmental preservation, or social security (Sun and Yang, 2020). Local Chinese governments make GARs available on public websites as part of their communication and transparency strategies. Recent study on GARs has concentrated on their effect on governmental conduct and governance in the realm of public administration. For instance, according to the GARs of the Central Government from 1954 to 2013, Wen (2014) measured the attention of the central government to basic public services. Hou and Yang (2016) quantified the keywords of urbanization in provincial government work reports from 2002 to 2013, so as to reflect the government's will to promote urban development, and explained the mechanism of the government's will to promote urbanization.

In recent years, governments at all levels, especially the central government, have been forced to pay more attention to environmental protection by enacting a series of new laws and regulations and ever-stricter enforcement (Liu and Wang, 2018; Shi et al., 2019). However, the existing research on government attention is mostly limited to public services and urban management, and few papers in the literature involve ecological or environmental management. More work needs to be done to investigate the effects of the government's attention to ecological and environmental governance, and answer the question: The focus of the government's environmental attention brings human, material, and financial resources related to policy implementation, in order to promote the improvement of policy implementation (Cheng and Liu, 2018; Zhang et al., 2021), so will the increased attention of the government result in an improvement in environmental quality? We thus contribute to addressing this evidence gap by studying how changes in the government attention in environment issues relate to improvements in environment quality. It is important to understand how environment attention gained from governments matters in terms of environment regulation.

The aim of this study is to empirically examine whether and to what extent the government attention affected environmental quality, especially local air pollution. To begin, we quantify the government's attention to the environment as coded by word frequency as it appears in GARs based on the WinGo Textual Analytics Database, which was utilized to conduct a longitudinal research using textual content analysis. Second, we conducted a series of spatial autocorrelation analysis to validate the existence of spatial effects in air pollution. We then determined the most plausible spatial economic model using Bayesian posterior model probability. Third, Spatial Durbin Model (SDM) was adopted to analyze the relationship between government attention and the environmental pollution represented by three air quality indices. Finally, we further validate our results at provincial level and investigate the regional impacts of government attention on the environment in different regions.

This study adds fresh quantitative evidence on political attention allocation through the analysis of a large dataset, which is particularly unusual in the field of environmental pollution research. Until far, few studies have examined the effect of political attention on environmental quality at the municipal level. In this study, we used 1716 GARs to analyze the effect of Chinese governments' environmental focus on air pollution throughout a six-year period (2014–2019), during which air pollution became a national policy concern in China. Additionally, this study also expands our knowledge of the importance of government attention, both conceptually with regard to government attention in environmental governance and empirically with a methodology that incorporates geographical spillover effects into existing econometric assessment methods.

2. Data and methodology

This section begins by introducing the data sources and variables being measured. In what follows, we describe the methodology used for analysis.

2.1. Data and variables

We assemble a city-year level dataset covering 286 cities in the main estimation sample, for a period ranging from 2014 to 2019. We include data on air quality, government attention on the environment, and various city-level socioeconomic characteristic variables. The air-quality data is collected from the Ministry of Ecology and Environment of the People's Republic of China (PRC) (http://datacenter.mee.gov.cn/). The data of government attention on the environment as measured by the frequency of environment-related words appearing in GARs is extracted from the WinGo Textual Analytics Database (http://www.wingodata.com/). Other variables are collected from the China Regional Economic Research Database of CSMAR (https://www.gtarsc.com/). This section discusses our primary variables, its definitions and measurements.

2.1.1. Dependent variable: air quality

Three dependent variables are utilized in our study: yearly Air Quality Index (AQI), PM_{10}, and NO_2 concentration. We aggregated the 24-hour daily monitoring data to yearly level by city. Collectively, we obtained 1716 city-year observations. Notably, in our study, what we require is a model that allows us to estimate to what extent the percentage in air pollution changes in association with the variation in government attention allocation. Therefore, we transformed our dependent variables by using the natural logarithm to interpret estimated results in percentage terms.

2.1.2. Independent variables: environment attention

One of the most significant obstacles to studying political attention in China is a dearth of high-quality data on which to base systematic measures of local government attentiveness. Benefiting from the WinGo Textual Analytics Database, which collected nearly 6000 government textual files from GARs covering 20 years (2001–2020), we are able to conduct a longitudinal study of governments' attention to

Table 1
Key words selected in this study.

Key words in English	Key words in Chinese	Word frequency
Air quality	空气质量	3592
Atmospheric pollution	大气污染	2300
Blue sky	蓝天	1495
Blue sky and white clouds	蓝天白云	185
Centralized heating	集中供热	2076
Clean energy	清洁能源	2084
Dust	扬尘	1739
Emissions reduction	减排	3222
Energy consumption	能耗	6466
Environmental assessment	环评	474
Environmental protection	环境保护	6302
Environmental quality	环境质量	1557
Green development	绿色发展	3149
New energy	新能源	5568
Nitrogen oxides	氮氧化物	443
Particulate matter	颗粒物	110
Pollution control	污染治理	1743
Pollution prevention and control	污染防治	2881
Sulfur dioxide (SO_2)	二氧化硫	2022
The abbreviation of environmental protection	环保	9155
The abbreviation of pollution control	治污	1407

environmental pollution from 2014 to 2019 by utilizing textual content analysis, a systematic approach for translating qualitative information into quantitative data using defined frameworks for analysis. The method has been used to examine a range of issues including the attention given to climate change in Canada (Ahchong and Dodds, 2012), Mexico (Balderas Torres et al., 2020), and the USA (Liu et al., 2008). Specifically, we assessed the percentage of environment-related terms in GARs relative to the total number of words used as a surrogate for the explanatory variable. Table 1 details the process of material selection, coding, and retrieval.

2.1.3. Control variables

To account for socioeconomic drivers that may affect air pollution levels, we incorporate a battery of control variables into our model by following earlier research about air-pollution issues (Rodríguez et al., 2015; Ma et al., 2016; Hao and Liu, 2016; Zeng et al., 2019; Yue et al., 2019; Ren and Matsumoto, 2020), including per capita GDP, population density, the proportion of the added value of secondary industry to GDP, science and technology expenditure, road traffic, and province-level energy consumption.

The variables and their meanings, as well as descriptive statistics, are summarized in Table 2. To ensure that our findings are more practical and intuitive, we provide the raw data rather than the natural log data utilized in our regression study. As seen, the statistical findings for three pollution indicators demonstrated significant variance among cities. For example, the mean of PM_{10} (83.38 μg/m^3) is significantly higher than the WHO's 50 μg/m^3 criterion, with a low of 18.00 μg/m^3, a maximum of 371.00 μg/m^3, and a standard deviation of 32.28 μg/m^3.

2.2. Methodology

Spatial econometrics methodologies are gaining traction in the study of air pollution interactions, since researchers have demonstrated convincingly that both environmental and socioeconomic variables may contribute to the aggregation and diffusion of air pollutants (Hao and Liu, 2016; Feng et al., 2020; Vadrevu et al., 2020; Zhu et al., 2020; Ren and Matsumoto, 2020; Zeng and Bao, 2021). These findings imply that air pollution levels in a particular city may be influenced to some extent by its nearby cities. Kolak and Anselin (2019) noted that losing sight of spatial correlation might invalidate normal statistical processes, resulting in erroneous or inconsistent estimates, standard errors, and measures of fit. To solve this empirical difficulty, it is necessary to explore spatial econometrics in order to increase the efficiency and accuracy of our study. The spatial autocorrelation analysis, model selection, and empirical technique are discussed in this subsection.

2.2.1. Spatial weight matrix

The spatial econometrics literature is interested in the dependence among observations across space and uses the so-called spatial weight matrix $\boldsymbol{W}$ to describe the spatial arrangement of the geographical units in a given sample. The choice of appropriate spatial weights is a central component of spatial models. For our study, we employ a binary contiguity weight matrix to model the spatial dependence of the observations, whose elements represent the strength of spillovers between each pair of spatial units (Bhattacharjee and Jensen-Butler, 2013). In particular, we set W_{ij}=1 if city i and city j share a border line and 0 otherwise:

$$W_{ij} = \begin{cases} 1, bnd(i) \cap bnd(j) \neq \Phi \\ 0, bnd(i) \cap bnd(j) = \Phi \end{cases} \tag{1}$$

2.2.2. Spatial autocorrelation analysis

According to Tobler's first law of geography (Tobler, 1970), everything is related to everything else, but near things are more related to each other. Spatial weight matrix ($\boldsymbol{W}$), containing the spatial relations among observations, is commonly used to express Tobler's law. On this basis, we measure the spatial autocorrelation of the dependent variables by calculating Moran's index, which came about as a result of Pearson's correlation coefficient in general statistics. We then estimate two Moran's I indexes: Global Moran's I (GMI) and Local Moran's I (LMI). GMI and LMI test for global and local spatial correlation, respectively. The GMI is calculated as the follows:

$$GMI = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(Y_i - \overline{Y})(Y_j - \overline{Y})}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(Y_i - \overline{Y})^2 \sum_{i=1}^{n}(Y_i - \overline{Y})^2\right.}, (i \neq j) \tag{2}$$

Where n is the total number of spatial units; Y_i and Y_j stand for two air-pollution indicators of i th and j-th cities respectively. $\overline{Y}$ is the sample mean of the variable Y, and $\boldsymbol{W_{ij}}$ is the binary spatial weight matrix ($n \times n$) of the connection between the i th and j-th sample cities.

The values of Moran's I for the AQI index, PM_{10}, and NO_2 during the periods from 2014 through 2019 are shown in Table 3. The values range

Table 2
Decriptive statistics ($N = 1716$).

Variables	Definitions	Mean	SD.	Min	Max
AQI	Annual air quality index	81.80	22.91	18.00	230.00
PM_{10}	Annual PM_{10} concentrations (μg/m^3)	83.38	32.28	18.00	371.00
NO_2	Annual NO_2 concentrations (μg/m^3)	31.37	10.35	5.00	66.05
Enviro_atten	Proportion of environment-related words to total words of the GARs (%)	0. 96	0. 28	0. 21	2. 27
PGDP	Per capita GDP at current price (RMB Yuan)	57,553	32,671	10,171	203,489
Density	Proportion of total population (year-end) to administrative jurisdiction area (persons/km^2)	437.80	350.50	5.248	2713
Second	Proportion of secondary industry to GDP (%)	44.71	11.11	11.04	80.07
S&T expenditure	Proportion of local science and technology expenditure to budgeted local fiscal expenditure (%)	18.90	4.06	4.75	34.80
Traffic	Highway passenger capacity (10,000 persons)	22,105	41,909	171	477,180
Energy consumption	Coal consumption at provincial level (million tons)	188.17	93.91	18.20	413.90

Table 3
Results of GMI statistics.

Year	2014	2015	2016	2017	2018	2019
Ln_AQI	0.421***	0.758***	0.746***	0.668***	0.737***	0.750***
z	15.792	28.245	27.819	24.932	27.453	27.961
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Ln_PM$_{10}$	0.414***	0.757***	0.732***	0.643***	0.741***	0.705***
z	15.499	28.225	27.309	24.023	27.600	26.282
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Ln_NO$_2$	0.188***	0.431***	0.432***	0.418***	0.427***	0.463***
z	7.141	16.116	16.162	15.659	15.971	17.321
p-value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: This table reports the results of global spatial analysis. The values of GMI range from –1 (perfect dispersion) to +1 (perfect correlation). Larger magnitudes reflect stronger spatial correlations.

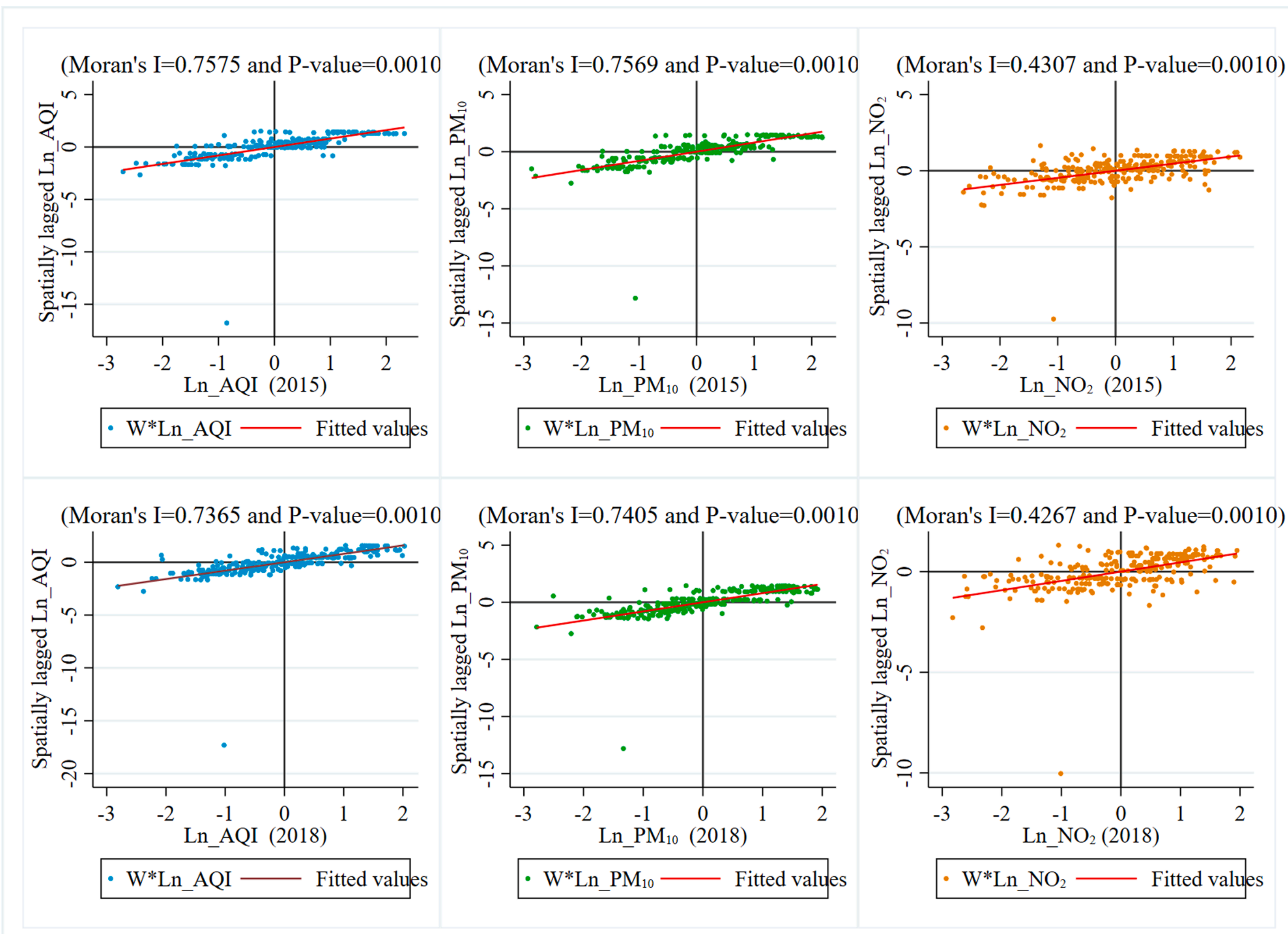

Fig. 1. City-specific Moran scatter plot for AQI and the concentrations of PM$_{10}$ and NO$_2$.Notes: This figure was generated with Stata 16.0 software. To save space, we offer graphical evidence for 2015 and 2018, respectively.

from 0.188 to 0.757, and all values are significant at the 1% level. This result indicates that air pollution exhibits a significant positive spatial autocorrelation. In other words, cities with high/low air-pollution emissions are clustered in space.

We also considered the LMI for each spatial unit and evaluated the statistical significance for each *LMIi*. The general form of LMI is written as:

$$LMI_i = \frac{\mathrm{n}(Y_i - \overline{Y})}{\sum_{i=1}^{n}(Y_i - \overline{Y})^2} \sum_{j \neq i}^{n} W_{ij}\left(Y_j - \overline{Y}\right) \tag{3}$$

In which all variables have the same meanings as in formula (2).

Based on the LMI, the Moran scatter in Fig. 1 plots different air-pollution indicators against their spatial lag. As depicted, the plot is partitioned into four quadrants, which represent four different types of spatial relations among observations. We observed that Moran scatter are almost equally distributed in Quadrants I and III, indicating that air-pollution concentrations are spatially and positively correlated among the spatial units – the cities with high air-pollution concentrations (or low air-pollution concentrations) appear close to each other, or clustered together, in space. This finding provides supportive evidence that air pollutants were clustered in space.

To provide a more intuitive demonstration, we further provide

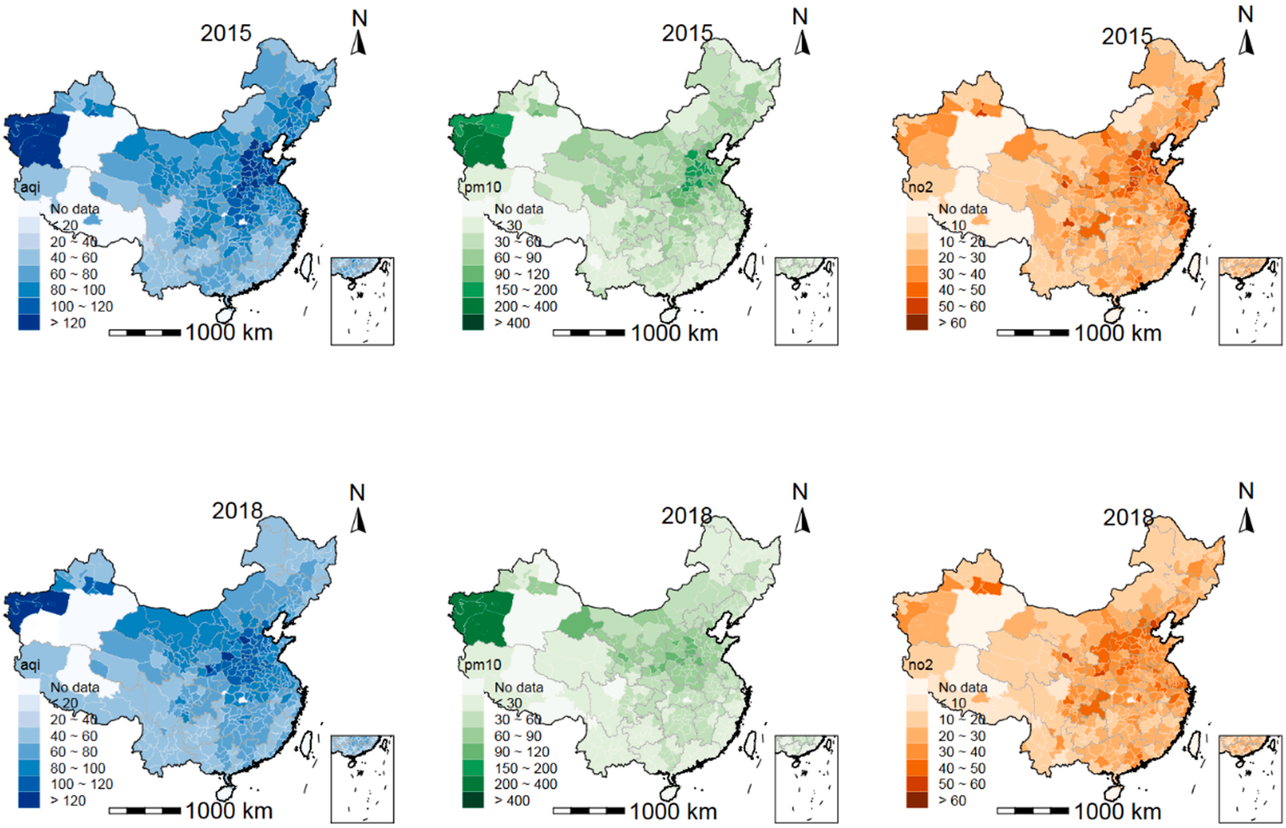

Fig. 2. Geographical distribution for AQI and the concentrations of PM_{10} and NO_2. These figures were generated with Stata 15.0 software.

Table 4
Simultaneous Bayesian comparison of model specifications.

Models	*Ln_AQI*	*Ln_PM₁₀*	*Ln_NO₂*
SAR_probs	0.1407	0.0443	0.0041
SEM_probs	0.0000	0.0000	0.0000
SDM_probs	*0.8593*	*0.9557*	*0.9957*
SDEM_probs	0.0000	0.0000	0.0000

Note: The highest probability in each column is in italics and the probabilities in each block sum to 1.

geography-based evidence for the spatial clustering pattern of AQI, PM_{10}, and NO_2 at city-specific level in Fig. 2. As illustrated, heavy air pollution was mainly concentrated in northern China, such as the Jing-jin-ji (Beijing, Tianjin, Hebei province) metropolitan area or the Yangtze River Delta city cluster. These patterns are consistent with the scatter plot in Fig. 1.

2.2.3. Spatial model selection

Using the latest spatial econometric techniques and data pertaining to 286 APL cities from 2014 to 2019, this article tests and compares four frequently-used spatial econometric models, i.e. Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), Spatial Durbin Model (SDM), and Spatial Durbin Error Model (SDEM), thereby following (Yesilyurt and Elhorst, 2017). As shown, we calculated the Bayesian posterior model probabilities for the different model specifications in Table 3. With these probabilities we can simultaneously determine the most likely spatial econometric model.

The results in Table 4 show that the SDM model outperforms the other models in all 12 cases, for all three air-pollution indicators. Probabilities for the SDM model range from 0.8593 to 0.9957. This finding corroborates previous approaches by Zhou et al. (2021), indicating that the spatial interaction among cities appears to be driven both by the endogenous spatial lag and other variables observed in neighboring cities.

2.2.4. Spatial econometric analysis

This section develops a SDM model based on Bayesian posterior model probabilities, which is widely used for modeling air pollution. The model is motivated by the empirical facts cited in the previous section and shows that both the dependent and independent variables and their spatial lagged terms are included when capturing the inherently spatially-interactive nature of air pollution in local cities and their neighboring cities. Specifically, we present Spatial Durbin Model (SDM) below:

$$Ln\left(Air\_quality\right)_{i,t} = \rho W_{i,j} Ln\left(Air\_quality\right)_{i,t} + \beta_0 \mathrm{Envion\_Attent}_{i,t} + \beta_1 CV_{i,t} + \beta_2 \sum_{j=1}^{n} W_{i,j} \mathrm{Envion\_Attent}_{i,t} + \beta_3 \sum_{j=1}^{n} W_{i,j} CV_{i,t} + City_i + Year_t + \varepsilon_{i,t} \tag{4}$$

In which, the variable $\mathrm{Ln}(Air\_quality)_{i,t}$ is our outcome variable, including three measures of air pollution of city i in year t. the variable $W_{i,j}Ln(Air\_quality)_{i,t}$ denotes the interaction effect of the dependent variable $\mathrm{Ln}(Air\_quality)_{i,t}$ with the dependent variables in neighboring units, $\rho$is the spatial autocorrelation coefficient; W_{ij} is the i, j-th element of a pre-specified nonnegative $N \times N$ binary spatial contiguity weight matrix, describing the arrangement of the spatial units in the sample. $Environ\_attent_{i,t}$ represents independent variables of our interest, capturing the effects of environmental attention on air pollution; $\sum_{j=1}^{n} W_{i,j}\mathrm{Envion_Attent}_{i,t}$is its spatially-lagged term, capturing the effects of environmental attention in neighboring cities on air pollution. $CV_{i,t}$ is a $N \times 6$ vector of control variables, $\sum_{j=1}^{n} W_{i,j} CV_{i,t}$ is its spatially-lagged term. $City_i$ captures spatial fixed effects. $Year_t$ captures temporal fixed effects. $\varepsilon_{i,t}$ is normally-distributed errors.

Table 5
Main results of SDM model.

Variables	(1)*Ln_AQI*	(2)*Ln_PM$_{10}$*	(3)*Ln_NO$_2$*
*W*Ln(Air_quality)*	0.614***	0.561***	0.452***
	(0.022)	(0.025)	(0.031)
Enviro_atten	-0.039***	-0.043**	-0.072***
	(0.014)	(0.018)	(0.018)
Ln(PGDP)	-0.148***	-0.196***	-0.061
	(0.047)	(0.060)	(0.060)
Ln(Density)	0.480	-0.072	-1.156
	(0.774)	(0.990)	(0.999)
Ln(Second)	0.003***	0.003**	0.000
	(0.001)	(0.002)	(0.002)
Ln(S&T expenditure)	0.042	0.007	0.190
	(0.177)	(0.227)	(0.229)
Ln(Traffic)	-0.001	0.003	0.010
	(0.011)	(0.014)	(0.014)
Ln(Energy consumption)	-0.011	-0.036**	-0.019
	(0.014)	(0.018)	(0.018)
W_x	Yes	Yes	Yes
Spatial fixed effects	Yes	Yes	Yes
Temporal fixed effects	Yes	Yes	Yes
Observations	1716	1716	1716
LogL.	1273.981	863.707	865.784
R-squared	0.024	0.006	0.003

Notes: Standard errors in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. For the sake of simplicity, the results of spatially-lagged independent variables are not reported here, but are available upon request.

3. Estimation results

We now analyze the results of the spatial estimates of the relationship between environmental attention and air pollution.

3.1. Baseline regression

3.1.1. Main results

Table 4 summarizes the major findings from our baseline regressions. All models use geographical and temporal fixed effects. With 1716 city-year observations, it was determined that the generated models accurately represented the data profiles.

The coefficients of the lagged-dependent variable in space (ρ) are all significantly positive at the 1% level, showing the presence of spatial impacts of air pollution. *Environ_atten* has coefficients of –0.039, –0.043, and –0.072 on AQI index, PM_{10}, and NO_2 concentrations, respectively, and all are statistically significant at the 5% level or higher. The findings indicated that variation in environmental attention was associated with large variations in air pollution.

Numerous empirical research, as seen in Table 5, employ point estimates to test the concept of geographical spillovers. However, LeSage and Pace (2009) pointed out that doing so may result in incorrect results due to the absence of the marginal influence of certain changes in independent variables. Calculating the estimated direct and indirect impacts is still important. As a result, we obtain the marginal effects of the explanatory variables listed below.

3.1.2. Marginal effects

We now compute the marginal impact using the two-way fixed effects SDM specification by taking into account the geographical spillover effect of the dependent and independent variables via the weight matrix's shape. The estimation results are summarized in Table 6. As indicated, environmental attention's anticipated direct and indirect effects on air pollution emissions were negative at the 5% level, as expected. To be more precise, a 1% increase in government attention to the environment results in a 4.2%, 4.5%, and 7.4% drop in the AQI index, PM_{10}, and NO_2 concentrations, respectively, while all other variables held constant. In the instance of the indirect effect, surrounding cities' environmental attention allocation results in a 5.8%, 5.18%, and 5.68% drop in three air-pollution indicators.

3.2. Robustness check

To illustrate further the robustness of our baseline results, we conduct a battery of robustness check and sensitivity analysis. We begin by calculating the median values of three air-pollution indicators as alternative measures of the dependent variables. The estimation results are displayed in Columns (1) – (3) of Table 7. As shown, the coefficients of *Enviro_atten* are smaller than the earlier findings, but remain significant at the 10% level or higher. This is understandable for the difference in calculation method. We then use the proportion of environment-related sentences appearing in GARs to total of textual sentences to proxy the attention allocation that governments applied to environmental issues. We report the estimated results in Columns (4) – (6) of Table 6. A consistent result can be obtained, indicating that more government attention on air pollution accurately predicted a less pollution concentration. Overall, these findings suggest that our baseline regression results are robust.

We then used an alternative spatial weight matrix test to further confirm the validation of our baseline results. There are multiple ways to define if a spatial unit is within the proximity of a city. In baseline

Table 6
Average direct and indirect effect estimates.

Variables	Direct effects			Indirect effects		
	(1)*Ln_AQI*	(2)*Ln_PM$_{10}$*	(3)*Ln_NO$_2$*	(1)*Ln_AQI*	(2)*Ln_PM$_{10}$*	(3)*Ln_NO$_2$*
Enviro_atten	-0.042***	-0.045**	-0.074***	-0.058**	-0.051**	-0.056***
	(0.016)	(0.020)	(0.020)	(0.022)	(0.023)	(0.016)
Ln(PGDP)	-0.142***	-0.192***	-0.059	0.128	0.123	0.093
	(0.043)	(0.055)	(0.056)	(0.094)	(0.110)	(0.094)
Ln(Density)	0.917	0.337	-1.200	5.972	5.589	-3.345
	(0.803)	(0.993)	(0.964)	(5.485)	(6.209)	(5.075)
Ln(Second)	0.003***	0.003**	-0.000	-0.008*	-0.005	-0.012***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)	(0.004)
Ln(S&T expenditure)	0.058	0.024	0.202	0.269	0.324	0.293
	(0.163)	(0.208)	(0.212)	(0.344)	(0.401)	(0.350)
Ln(Traffic)	-0.008	-0.003	0.007	-0.128**	-0.136**	-0.090*
	(0.012)	(0.014)	(0.014)	(0.059)	(0.066)	(0.054)
Ln(Energy consumption)	-0.012	-0.036*	-0.021	-0.004	-0.003	-0.051
	(0.016)	(0.020)	(0.019)	(0.080)	(0.091)	(0.074)

Notes: Standard errors in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7
Alternative dependent and independent variable.

Variables	Alternative dependent variable(Median)			Alternative independent variable(environmental sentences)		
	(1)*Ln_AQI*	(2)*Ln_PM₁₀*	(3)*Ln_NO₂*	(4)*Ln_AQI*	(5)*Ln_PM₁₀*	(6)*Ln_NO₂*
*W*Ln(Air_quality)*	0.502***	0.524***	0.413***	0.615***	0.563***	0.454***
	(0.028)	(0.027)	(0.032)	(0.022)	(0.025)	(0.031)
Main _results	-0.017**	-0.021**	-0.029**	-0.024*	-0.031*	-0.058***
	(0.008)	(0.010)	(0.012)	(0.013)	(0.017)	(0.017)
Direct_effects	-0.018**	-0.021*	-0.029**	-0.026*	-0.032*	-0.059***
	(0.009)	(0.011)	(0.013)	(0.015)	(0.018)	(0.018)
Indirect_effects	-0.016**	-0.021*	-0.019**	-0.036*	-0.037*	-0.045***
	(0.008)	(0.011)	(0.009)	(0.021)	(0.021)	(0.015)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
W_x	Yes	Yes	Yes	Yes	Yes	Yes
Spatial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Temporal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1716	1716	1716	1716	1716	1716
LogL.	2297.000	1839.578	1539.920	1271.926	862.653	863.994
R-squared	0.356	0.334	0.022	0.027	0.002	0.003

Notes: Standard errors in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

regression, we defined the spatial weight matrix based on contiguity. We now define an alternative spatial weight matrix based on distance. Columns (1) – (3) in Table 7 show the estimated results. The coefficients for *Enviro_atten* are all significantly negative. The findings support the baseline regression results based on spatial binary contiguity weight matrix.

As Beijing, Tianjin, Shanghai, and Chongqing are in line with provincial units in terms of administrative level, there is a significant difference between these four metropolises, and other general APL cities in economic-development levels, population scale, and pollution patterns. For example, Chongqing, with a higher air pollution level, consists of 26 districts and 12 counties, covers an area of some 82.4 thousand km^2, as big as the United Arab Emirates, and has a combined population of over 32 million, more than that of Australia. As a result, excluding these four municipalities may result in skewed regression findings. We thus excluded these four city samples from our robustness check. Table 8's Columns (4) – (6) detail the projected outcomes. These results provide evidence consistent with Tables 5 and 6.

Finally, given that the variations in the concentration of air pollutants are strongly influenced by meteorological factors (Bao and Zhang, 2020; Zeng and Bao, 2021), as a way of addressing this concern, we collect annual average temperature, annual sunshine duration, annual amount of precipitation, and annual average wind speed from the China Meteorological Administration website. We then appended the data into our original dataset and implemented the same analyses. The estimated results with multiple meteorological factors under control are shown in Table 9. These results illustrate that our baseline finding is not biased by any omitted meteorological variable.

4. Additional analysis

In this section, we are to examine the possible effects of government attention on environmental agenda and investment. It should be pointed out that we are only able to provide an auxiliary validation at provincial level due to the lack of city-level data. More persuasive evidence at city level needs larger future research endeavor. We then investigate the variability of its effects on air pollution in distinct places.

4.1. Auxiliary validation at provincial level

In theory, attentional process involves not only this notion of attention as "noticing" but also the process of intentional, sustained allocation of cognitive resources to guide problem solving, planning, sensemaking, and decision-making (Pinkse and Gasbarro, 2019). Extant research finds that there is a high likelihood that these intentions are translated into policy outputs further down the policy-making chain (Kelso, 2017). On this basis, we argue that increases in government attention in environmental arenas will intensify the policy agenda-setting on environment regulation. At the same time, many research papers have established the link between environmental regulation and pollution mitigation. As discussed in Zeng et al. (2019) and Zeng et al. (2021), emission from energy consumption is the main

Table 8
Substituting spatial weight matrix and eliminating outliers.

Variables	Alternative spatial weight matrix			Eliminating outliers		
	(1)*Ln_AQI*	(2)*Ln_PM₁₀*	(3)*Ln_NO₂*	(4)*Ln_AQI*	(5)*Ln_PM₁₀*	(6)*Ln_NO₂*
*W*Ln(Air_quality)*	2.959***	2.358***	0.872***	0.609***	0.553***	0.450***
	(0.059)	(0.044)	(0.049)	(0.023)	(0.025)	(0.031)
Main _results	-0.038***	-0.051***	-0.060***	-0.037***	-0.040**	-0.069***
	(0.014)	(0.018)	(0.019)	(0.014)	(0.018)	(0.019)
Direct_effects	-0.038**	-0.053***	-0.061***	-0.046***	-0.050**	-0.070***
	(0.015)	(0.020)	(0.021)	(0.015)	(0.019)	(0.019)
Indirect_effects	0.057**	0.090***	-0.394	-0.148**	-0.190**	-0.048
	(0.023)	(0.033)	(2.361)	(0.069)	(0.078)	(0.064)
Wx	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Spatial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Temporal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1716	1716	1716	1692	1692	1692
LogL.	1250.620	842.156	816.422	1246.439	842.044	845.493
R-squared	0.059	0.045	0.060	0.014	0.002	0.003

Notes: Standard errors in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 9
Considering meteorological factors.

Variables	(1)*Ln_AQI*	(2)*Ln_PM*$_{10}$	(3)*Ln_NO*$_2$
*W*Ln(Air_quality)*	0.608***	0.558***	0.446***
	(0.023)	(0.025)	(0.031)
Main _results	-0.036**	-0.040**	-0.067***
	(0.014)	(0.018)	(0.018)
Direct_effects	-0.041***	-0.048**	-0.068***
	(0.016)	(0.020)	(0.019)
Indirect_effects	-0.087	-0.157*	-0.041
	(0.081)	(0.092)	(0.074)
Ln(Sunshine)	0.061	0.048	0.225
	(0.121)	(0.155)	(0.156)
Ln(Precipitation)	0.008	0.020	-0.132**
	(0.041)	(0.052)	(0.052)
Temperature	-0.040**	-0.034	0.023
	(0.018)	(0.023)	(0.023)
Wind_speed	-0.043*	-0.056*	-0.055*
	(0.023)	(0.029)	(0.029)
Wx	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Spatial fixed effects	Yes	Yes	Yes
Temporal fixed effects	Yes	Yes	Yes
Observations	1716	1716	1716
LogL.	1280.592	868.259	876.414
R-squared	0.000	0.001	0.003

Notes: Standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

contributor to air pollution. Thus, governmental energy-control policies may lead to large reductions in air pollutant emissions. These findings provide a foundation for us to examine the potential mechanisms behind the relationship between government attention and air pollution.

To be specific, we consider three observable variables as the measure of policy outputs according to the preceding research (Zeng et al., 2019, 2021): in particular, the number of emission-reduction policies aiming to reduce emissions from the source (such as elimination of outdated vehicles) and renewable-energy policies dedicated to the development and promotion of renewable energy (such as solar, wind, biomass, geothermal), total environmental investments spent in pollution control. Due to the lack of city-level data, we focus on a provincial-level analysis. The estimated results are reported in Table 10.

Our empirical findings imply that environmental attention has a range of effects on the outcomes of environmental policy. In Columns (1) – (4), we examine the effect of two different types of energy policies on environmental attention as assessed by the frequency of words and sentences including environmental concerns. We discover that environmental concerns have a large effect on renewable energy policies but have no discernible effect on emission-reduction initiatives. This disparity might be explained by the greater costs of implementing emission-reduction strategies, as a significant amount of economic development is typically generated by businesses and organizations that are also large pollutants. Shutting down an excessive number of polluting businesses will place executive pressure on local officials, particularly those facing an aggressive GDP target under the Target Responsibility System (TRS). On the contrary, implementing renewable energy regulations has the potential to boost economic growth while also reducing pollution. This environment enabled reasonable economic decision-makers to encourage renewable energy development. Columns (5) – (6) examine the effects of attention allocation on environmental regulation investment. Environmental attention, our calculations indicate, has a statistically significant and positive effect on environmental investment.

Of course, we proceed cautiously with these putative processes because we present evidence for just 31 provincial administrations. Nonetheless, our findings revealed that rising environmental agenda setting and pollution control investments are strongly associated with increased government attention.

4.2. Regional effects analysis

In this subsection, we turn our attention to potential regional effects. As has been studied, the air pollution situation is more severe in northern and northeastern China than in southern China owing both to specific emission sources and meteorological conditions (Zeng et al., 2019). An example is winter heating in northern China, which has been regarded as a critical contributor to air pollution (Almond et al., 2009; Zheng et al., 2020; Weng et al., 2021). Northern cities thus are considered as high-priority regions for curbing air pollution. In recent years, the Chinese government has launched a series of policies (such as a clean-heating policy) and comprehensive plans (such as *China's Air Pollution Prevention and Control Action Plan*) aimed at preventing air pollution in northern China. More environmental attention has clearly been spent on northern cities. Here we investigate whether the effects of environmental attention varied by region. Our dataset contains 286 cities, 140 of which are located in the south and 146 in the north. To test for the north-south differences, we stratified our data by location and reran our SDM model. The estimated findings are shown in Table 10.

As expected, we detected a negative connection between environmental attention and air pollution levels in both northern and southern cities. On average, a one unit increase in environment attention led a -4.7%, -5.3%, -7.9% drop in AQI index, PM_{10} and NO_2 concentrations in northern cities. In the case of the northern cites, a one unit increase in environment attention is associated with a -5.5%, -6.4%, 5.2% drop in three pollutants, respectively. These findings demonstrate that the effects of government attention to air pollution vary according to geography and kind of air pollutant. The findings also suggest that the effects of environmental attention on the AQI index and PM_{10} are substantially less in northern cities that have historically high levels of pollution than in their southern equivalents. In comparison, the impacts of environmental attention on NO_2 were stronger in northern cities than in southern cities. In general, our findings indicate that greater effort should be made to manage air pollution in northern cities, and that diverse solutions should be implemented to deal with various air contaminants.

Table 10
Mechanism analysis.

Variables	(1)*Ln_Renew*	(2)*Ln_Renew*	(3)*Ln_Reduc*	(4)*Ln_Reduc*	(5)*Ln_Invest*	(6)*Ln_Invest*
Enviro_atten1	49.587*		-9.980		71.197**	
	(24.406)		(16.319)		(30.232)	
Enviro_atten2		3.707**		0.032		4.997**
		(1.408)		(1.164)		(2.112)
Constants	6.615	6.835	-13.468**	-13.346**	-12.841***	-12.775***
	(8.346)	(8.319)	(5.331)	(5.346)	(3.201)	(3.189)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	No	No
Observations	434	434	434	434	434	434
R^2*_w*	0.775	0.777	0.958	0.958	0.759	0.760

Table 11
Regional effects analysis.

Variables	Northern cities			Southern cities		
	(1)*Ln_AQI*	(2)*Ln_PM_{10}*	(3)*Ln_NO_2*	(4)*Ln_AQI*	(5)*Ln_PM_{10}*	(6)*Ln_NO_2*
*W*Ln(Air_quality)*	0.588***	0.538***	0.356***	0.501***	0.380***	0.445***
	(0.030)	(0.033)	(0.046)	(0.040)	(0.049)	(0.044)
Main _results	-0.047**	-0.052**	-0.080***	-0.043**	-0.052**	-0.046*
	(0.020)	(0.025)	(0.026)	(0.020)	(0.026)	(0.026)
Direct_effects	-0.047**	-0.053**	-0.079***	-0.055***	-0.064**	-0.052**
	(0.022)	(0.027)	(0.027)	(0.021)	(0.027)	(0.026)
Indirect_effects	-0.014	-0.031	0.005	-0.253***	-0.308***	-0.146
	(0.087)	(0.096)	(0.073)	(0.078)	(0.084)	(0.090)
Wx	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Spatial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Temporal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	876	876	876	840	840	840
LogL.	614.720	432.362	414.833	683.685	464.368	481.441
R-squared	0.017	0.068	0.007	0.018	0.167	0.117

Notes: Standard errors in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5. Conclusions and implications

This paper applies a political theory, attention, to the issue of environmental regulation. We reasoned that because the government's attention is limited, the executive must prioritize the government's agenda for the issues it deems most critical. On this premise, a widespread assumption is that fluctuation in the amount of government attention paid to environmental concerns may be used to forecast changes in environmental pollution levels. GARs, as official guidance papers, are critical in determining which policy concepts and topics make it into the macropolitical agenda in China. Using credible data on the attention and priorities of Chinese governments, we quantified the level of change in government environmental attention and examined the influence of government attention on mainland China's air pollution regulations. A series of spatial analysis established that air pollution has spatial spillover consequences. On this premise, SDM was used to represent the intrinsically dynamic, interacting nature of air pollution on a regional and temporal scale. The findings imply that increased government attention to the environment resulted in lower levels of air pollution. And according to additional analysis, the effect of government attention differed by region.

As evidenced by our findings, this study has a few consequences for the formulation of public policy objectives and environmental legislation. First, government attention to environmental concerns may be critical for air pollution management. If a municipal government want to improve the quality of its environment, policymakers need to pay greater attention to specific environmental challenges. The government should identify and prioritize environmental concerns, as well as adopt policies to solve them. Not only is it critical to monitor the passage of environmental legislation and regulations, but also to assess and promote the inclusion of environmental actions in government plans and policy agendas, as these define the priorities and resources allocated during the practical process of policy adoption and implementation. Second, as our empirical research indicates, government attention has a large effect on the adoption of renewable energy legislation and results in higher investment in pollution management. Thus, in order to address the enduring problem of air pollution, the government should stimulate the growth of renewable energy and increase financial investment in pollution management. Third, given the heterogeneity of the impacts identified in our study, environmental goals and strategies should differ by region to maximize the efficacy of air pollution reduction.

This study also has certain limitations that should be noted. First, assessing government environmental sensitivity by the frequency of environmental phrases in local GARs may be problematic. Specific ecological preservation efforts, such as leadership directives, inspection, and participation in demonstration cities, may be included as additional measuring bases in future research. Second, this paper makes no mention of the effect of local government officials' personal characteristics on the link between local government environmental attention and environmental policy execution. Additional factors influencing the link, as well as the intermediary pathway connecting government concern with pollution reduction, may be examined in future study. Thirdly, we could only examine the short-term effects of government attention to air pollution since data on environmental outcomes and socioeconomic determinants were not available prior to 2014. Fourthly, it is quite probable that a city would implement additional environmental rules in order to avoid and regulate pollution. Due to financial and time restrictions, it is outside the scope of this research to acquire necessary information concerning policy adoption at the municipal level; therefore, we analyze potential mechanisms for reducing pollutant emissions at the provincial level. Future research should gather data at the municipal level to assess and validate the effect of government attention allocation on policy adoption and implementation in the environment.

CRediT authorship contribution statement

Rui Bao: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing. **Tianle Liu:** Methodology, Investigation, Writing – original draft.

Declaration of Competing Interest

None.

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