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SPECIALTY SECTION
This article was submitted to
Environmental Economics and
Management,
a section of the journal
Frontiers in Environmental Science

RECEIVED 03 October 2022
ACCEPTED 31 October 2022
PUBLISHED 21 November 2022

CITATION
Zhang L, You S, Zhang M, Zhang S, Yi S
and Zhou B (2022), The effects of
urbanization on air pollution based on a
spatial perspective: Evidence
from China.
Front. Environ. Sci. 10:1058009.
doi: 10.3389/fenvs.2022.1058009

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The effects of urbanization on air pollution based on a spatial perspective: Evidence from China

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The severity of haze pollution has increased along with the growth of the economy and urbanization. Studying the relationship between urbanization and environmental pollution is extremely important from a practical standpoint in the context of encouraging new urbanization development in China. In this paper, we explore the impact mechanism of urbanization on air pollution, using a spatial Durbin model (SDM) build on panel data of 277 cities from 2010 to 2019. The findings demonstrate that urbanization significantly inhibits haze pollution across the country, with energy consumption structure and industrial structure upgrading acting as mediating factors. Moreover, economic growth, population aggregation, and openness to foreign investment aggravate pollution, whereas transportation facilities, urban vegetation areas, and wind speed reduce air pollution. Furthermore, foreign direct investment increases pollution nationwide while alleviating haze pollution in the eastern region. According to analysis of regional heterogeneity, there is a nonlinear relationship between urbanization and pollution in the central and western cities, while development and pollution in the eastern cities show a tendency to decouple. On this basis, this paper puts forward some policy recommendations to attenuate the vicious linkage between urbanization and pollution in order to promote high-quality urbanization development.

KEYWORDS

urbanization, air pollution, spatial Durbin model (SDM), nighttime light data (NTL), China

1 Introduction

China had a tremendous economic growth following the economic reform and opening-up, and it has also become the world's nation with the fastest urbanization rate, which increased from 17.92 percent to 64.72 percent from 1978 to 2021. Urbanization has driven China's rapid economic growth and strengthened its competitiveness in international markets. Similar to other developing countries, China's urbanization is accompanied by the transformation of surplus rural population into city population and the transformation of the primary industry into secondary and tertiary industries. In this

process, people, resources, and wealth are gathered in cities. Although urbanization promotes infrastructure investment (Zhou et al., 2015), expands consumption market, and improves the income and education level of residents (Yuan, 2015; Choy and Li, 2017), it also increases the consumption of resources, in turn, causing environmental pollution problems (Hueglin et al., 2005; Stone, 2008). Urbanization brings about “big city disease” such as traffic congestion, energy shortage, and air pollution. The World Health Organization estimates that air pollution causes seven million premature deaths annually, and air pollution, especially haze pollution, has become an important hidden danger to residents’ health.

Numerous scholars have discussed the connection between urbanization and air pollution through different models. Liang et al. (2019) discovered a nonlinear relationship between environmental pollution and urbanization using a geographically and temporally weighted regression model. Du and Feng (2013) constructed a panel model with Kaya’s constant equation, which indicated a U-shaped curve relationship between urbanization and air pollution in developing countries. Jiao (2015) tested the relationship between urbanization and environmental pollution at different population sizes, it was found that the urbanization rate of small-population countries had a positive linear relationship with environmental pollution, the urbanization rate of medium-sized countries had a U-shaped relationship with environmental pollution, and the urbanization rate of large-population countries had an inverted U-shaped relationship with environmental pollution. Moreover, many literature works have studied the variables through which urbanization affects air pollution. Rahman and Alam (2021), who found that the use of clean energy improved air quality, studied the interaction between environmental pollution and economic growth, population density, clean energy, and opening-up during urbanization in Bangladesh. Yang et al. (2018) found that urbanization can promote the reorganization of the industrial structure, deteriorating the environment in the short term and benefiting the treatment of air pollution in the medium and long term. Mayer (1999) argued that population growth and land expansion are the main reason for air pollution caused by urbanization. Gao et al. (2016) found that population aggregation in urbanization has a more significant effect on environmental pollution than land expansion.

In the study related to air pollution, spatial dependence between cities needs to be taken into consideration, otherwise, the spillover effect of air pollution would be neglected and the haze diffused from neighboring cities will be regarded as being produced by local cities. As a result, the residual terms of econometric models are spatially correlated, leading to inconsistent coefficient estimates of the urbanization and air pollution, which may lead to incorrect conclusions. Therefore, more accurate econometric models need to be constructed.

Spatial econometric models can effectively identify spatial spillover effects. There is a large number of literature using spatial econometric models to study urbanization and air pollution. Yu (2021) constructed four new-type urbanization indicators related to economy, demography, society, and environment. He used a dynamic spatial panel error model (SPEM) empirically to analyze the new-type urbanization in the environment in China and found that new-type urbanization significantly improves energy efficiency and reduces pollution emissions. Liu et al. (2017) used cross-sectional data from 289 cities in China to construct a spatial Durbin model (SDM), which revealed that urbanization significantly increases air pollution, and the urbanization of neighboring cities has a greater impact on air pollution than the urbanization of the city itself. Du et al. (2019) found that both urban expansion and population agglomeration have negative impacts on air quality. Gan et al. (2021) used the GS3LS model to study urbanization in 287 cities in China and found an inverted U-shaped relationship between economic growth and haze pollution, and urbanization leads to air pollution by increasing the exuberant demand of urban residents. By establishing a spatial Durbin model (SDM), Zhang et al. (2017) believed that there is a positive effect of economic growth on the spillover effect of haze pollution in the eastern and western provinces of China, while the economic growth in the central region has a negative spillover effect of haze pollution.

Although the aforementioned literature used spatial econometric models to reduce the estimation bias caused by spatial correlation, it is still difficult to determine whether urbanization increases, decreases, or has a nonlinear relationship with air pollution. Therefore, we analyze the potential shortcomings in the current studies and make efforts to obtain more accurate results by refining the variables, samples, and models. We discovered that the following reasons could affect the regression estimator. 1) Most of the studies are based on provincial data. Compared to cities, provinces have huge geographical spans, making it difficult to control the influence of environmental factors such as rainfall and wind temperature within the region. Moreover, cities are the basic unit of most policy implementation. As there could be huge differences in urbanization patterns between cities in the same province, using provincial data will ignore these differences. Therefore, the urban data selected in this paper can better reflect the environmental, economic, and policy changes in the region, as well as provide more accurate results for the model. 2) The time span of the sample is comparatively long, and as a result, the coefficients reflecting the mixed effects of two phases: the rapid expansion of urbanization in the early years and the high-quality urbanization in recent years, confuses the results. Considering the systematic impact of COVID-19 on the urban environmental and economic

order, we select the time span from 2010 to 2019 as the sample, which exactly covers the decade of China's new urbanization strategy and can better reflect the impact of China's sustainable urban development strategy. 3) A large amount of literature uses sociological statistics such as the industrial structure, population structure, or urban area variable as a substitute for urbanization, which suffers from data distortion due to changes in statistical caliber. This paper uses nighttime lights (NTL) data as a proxy variable for urbanization, which can also eliminate potential endogeneity problems between variables while ensuring the consistency of statistical caliber. 4) At present, a large amount of literature, articles merely focusing on economic and social factors, ignore the influence of natural factors. In order to reduce the resulting bias, we include control variables such as temperature, precipitation, and wind speed in our model.

In conclusion, this paper selects panel data of 277 prefecture-level cities in mainland China from 2010 to 2019 as the research object, empirically analyzes the impact and mechanism of urbanization on air pollution during the decade after China's new urbanization, and uses a spatial econometric model to eliminate endogeneity among variables.

2 Materials and methods

2.1 The baseline model

Dietz and Rosa (1997) proposed the STIRPAT model based on the IPAT model, pointing out that environmental pollution is influenced by factors such as population, affluence, and technology. The panel of the STIRPAT model can be expressed as $I = aP^{b_1}A^{c_1}T^{d_1}e$, where I, P, A, and T denote environmental impacts population, affluence, and technology, respectively, and e represents the error term. Taking the natural logarithm on both sides of the equation, we obtain

$$\ln I_{i,t} = a + b \ln P_{i,t} + c \ln A_{i,t} + d \ln T_{i,t} + e_{i,t} \quad (1)$$

Considering that a major advantage of the STIRPAT model is that it can appropriately improve the influencing factors of the environment (Jin et al., 2022), we extend the equation based on STIRPAT Eq. 1 and construct a panel equation as follows:

$$\ln AP = \beta_0 + \beta_1 \ln Urban_{i,t} + \lambda_{i,t} X_{i,t} + \varepsilon_{i,t} \quad (2)$$

where $\ln AP$ is the natural logarithm of air pollution concentrations in city i in year t , $\ln Urban$ represents the urbanization, X is a series of control variables including the economy, environment, and technology, and $\varepsilon_{i,t}$ is the error term.

Base on the STIRPAT model (Dietz & Rosa, 1994) and the EKC hypothesis (Grossman & Krueger, 1995), we extend Eq. 2 to Eq. 3 by selecting appropriate control variables with reference to (Yu et al. 2021) and (Shao S 2019).

$$\begin{aligned} \ln AP_{i,t} = & \beta_0 + \beta_1 \ln Urban_{i,t} + \beta_2 \ln Wind_{i,t} + \beta_3 \ln Rain_{i,t} \\ & + \beta_4 \ln Temp_{i,t} + \beta_5 \ln Green_{i,t} + \beta_6 \ln Metro_{i,t} \\ & + \beta_7 \ln Pop_{i,t} + \beta_8 \ln FDI_{i,t} + \beta_9 \ln Inv_{i,t} + \beta_{10} \ln Trans_{i,t} \\ & + \beta_{11} \ln GDP_{i,t} + \beta_{12} \ln Sec_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \end{aligned} \quad (3)$$

where β_1 is the regression coefficient of the core explanatory variable urbanization, β_2 to β_{12} are the coefficients of control variables, and μ_i QUOTE and τ_t are the error terms for the fixed effects of urban i and year, respectively.

2.2 Variable selection

2.2.1 Explained variables

Air pollution ($\ln AP$): We use the annual average concentration of PM2.5 as an indicator of air pollution. The data were obtained from the Atmospheric Composition Analysis Group of Washington University in St. Louis¹, which estimates annual and monthly ground-level fine particulate matter (PM2.5) for 1998–2020 by combining aerosol optical depth (AOD) retrievals from the NASA MODIS, MISR, and SeaWiFS instruments with the GEOS–Chem chemical transport model (Aaron van Donkelaar 2021). Also, considering that air pollution also includes sulfide, nitrogen oxides, and carbon monoxide, we will use the air quality index (AQI) from 2013 to 2019 for robustness analysis.

2.2.2 Core explanatory variables

Urbanization ($\ln Urban_1$): Urbanization is the core explanatory variable in this paper. We use nighttime light (NTL) data to characterize the level of urbanization. The NTL data are obtained by the satellite technology and are barely disturbed by natural and human factors and maintain the consistency and comparability of the data (Liu et al., 2021). Moreover, the NTL data reflect the economic development through the digital number (DN) value of each pixel from cities, and the expansion of the city area is also expressed by the changes between the area with a non-zero DN value. In addition, since the long-standing household registration system in China restricts population mobility, using population indicators as a proxy for urbanization would result in an underestimation of urbanization levels; moreover, scholars have demonstrated that NTL data reflect well the process of urbanization (Liu et al., 2012). Therefore, this paper uses the mean DN value in pixel of the cities as a proxy variable for urbanization ($\ln urban_1$). The data are collected from the Global Nighttime Light Database (GNLD), which is constructed based on the National Oceanic and Atmospheric Administration

¹ <https://sites.wustl.edu/acag/datasets/surface-pm2-5/>

(NOAA), is derived from DMSP/OLS imagery data until 2013 and from VIIRS/DNB imagery data.

2.2.3 Control variables

To minimize omitted variable bias, we also set a series of urban control variables as follows.

Foreign direct investment (lnFDI): Foreign direct investment (FDI) could have both positive and negative effects on air pollution (Zhang and Luo, 2021), corresponding to the “Pollution Heaven Hypothesis” and the “Pollution Halo Hypothesis” (Tang et al., 2022). On the one hand, FDI will introduce high technology, and thus reduce resource consumption and pollutant emissions; on the other hand, for developing countries, foreign investment and trade have become methods for developed countries to transfer energy-intensive industries. For example, the trade between China and developed regions leads to large net inflows of carbon emissions, especially in the sectors of mechanical and electronic equipment and chemical products (Wang et al., 2020), which will increase environmental pollution. Therefore, FDI should be included in the model, and this paper uses the annual accomplished foreign investment and converts it to RMB according to the exchange rate of the year, and the data are sourced from the China City Statistical Yearbook.

Population density (lnPop): Population exacerbates energy consumption and traffic congestion and has a negative impact on air quality. We calculated the population per unit area of the city precincts to express the population density and collected the data from the China Urban Statistical Yearbook.

Transportation infrastructure (lnTrans): The better the construction of transportation infrastructure, the more effective it is in relieving traffic congestion and reducing air pollution. However, excellent transportation infrastructure can also cause a “siphoning effect” on transportation in neighboring cities, increasing the pressure on the local road network and nearly worsening air quality (Sun et al., 2019). This paper uses the road freight volume to measure transportation infrastructure, and the data sources are China City Statistical Yearbook and China Transport Statistical Yearbook.

Urban green coverage (Green): Urban vegetation can absorb particulate matter to some extent and alleviate air pollution. This paper introduces urban green coverage to measure the degree of greening in cities, and the data are downloaded from CEI data².

Rail transit (Metro): The opening of urban rail transit has a significant and robust pollution control effect (Liang and Xi, 2016). Rail transit as an important public transportation facility can effectively replace the travel mode of road transportation such as private cars, and thus reducing tailpipe emissions and reducing air pollution. In this paper, the number of completed metro miles is used as a control variable, and the data source is

the Rapid Report on Rail Transit reported by the Ministry of Transport of China.

Climate variables: Wind speed (lnWind), rainfall (lnRain), and temperature (lnTemp), as important factors of climate change, can significantly affect the generation and dispersion of air pollution such as haze. Meteorological data are obtained from the China Meteorological Data Service Center³.

The economic development (lnPgdp): Economic development could intensify the resource consumption of residents and cause the gathering of polluting industries or guide enterprises to upgrade their industries through the income effect and provide more tax revenue for the government to support environmental protection and technology development, and thus affect air quality from both sides. Therefore, we choose GDP per capita to control the impact of economic development on air pollution, and the data are downloaded from CEI data.

Industrial structure (lnSec): The initial stage of urbanization is usually accompanied by industrialization, along with a large amount of waste gas and wastewater emissions. If the economic growth is mainly driven by the energy-intensive secondary industry, the air pollution in that city is more serious (Yu, 2010). In order to control the impact of the industrial structure on air quality, we selected the share of secondary industry output in regional GDP as one of the control variables.

2.2.4 Mediator variables

In order to explore the mechanism of urbanization inhibiting air pollution, we also test the mediating effect of two variables: industrial structure upgrading (ISU) and energy consumption structure (ECS). Referring to the previous studies, the ISU index is calculated by the economic proportion of each industry and the proportion of the employed population (Fu, 2010), and ECS is represented by the proportion of natural gas use in total energy (shao et al., 2019). All the data are collected from the China City Statistical Yearbook and China Energy Statistical Yearbook.

2.2.5 Descriptive statistics

This paper focuses on the impact of urbanization on haze pollution, and the data are municipal data which exclude county-level cities. To avoid heteroscedasticity, the logarithmic measurement is used for variables with absolute values. Table 1 shows descriptive statistics for each variable.

In order to observe the changes in air pollution in the past 10 years more intuitively, we take four of these years as samples to plot the changes of PM_{2.5} in prefectural-level cities in China⁴, as shown in Figure 1. It can be clearly found that haze pollution has obvious spatial aggregation, especially in North China and

² <https://ceidata.cei.cn/>

³ <http://data.cma.cn/>

⁴ The map template is from the Map Technology Review Center of the Ministry of Natural Resources (GS (2022) 4312)

TABLE 1 Descriptive statistics of variables.

Variable	Variable meaning	Unit	Obs	Mean	Std.DEV	Min	Max
lnAP	Annual mean of PM2.5	μm	2,770	3.725	0.359	1.150	4.687
lnUrban ₁	City light brightness value	—	2,770	-0.975	1.412	-4.819	3.038
lnWind	Urban average annual wind speed	m/s	2,770	0.733	0.228	0.006	1.426
lnRain	Urban average annual rainfall	mm	2,770	6.822	0.538	4.074	7.917
lnTemp	Urban mean annual temperature	°F	2,770	4.050	0.157	3.395	4.346
lnFDI	Foreign direct investment	10,000 Yuan	2,770	11.530	2.847	0	16.830
Metro	Metro operating mileage	km	2,770	12.870	64.570	0	809.900
Green	Urban green coverage	%	2,770	0.399	0.052	0.085	0.648
lnPop	Urban population coverage	person/km ²	2,770	7.657	1.080	3.894	11.040
Inv	Percentage of green inventions in the total number of patents obtained in the region	%	2,770	0.120	0.064	0.014	0.771
lnTrans	Road freight volume	10,000 tons	2,770	9.026	0.865	5.361	13.230
lnPgdp	Per capita GDP	Yuan	2,770	10.667	0.581	8.881	13.056
lnSec	Proportion of the secondary industry in GDP	%	2,770	3.834	0.276	2.330	4.497
ISU	Industrial structure upgrading index	—	2,720	6.505	0.347	5.517	7.836
ECS	Energy consumption structure	%	2,720	0.157	0.141	0	0.851

Sichuan Province. Therefore, the spatial correlation of haze pollution should be analyzed.

2.3 Spatial correlation analysis

Tobler’s first law of geography states that all attribute values on a geographic surface are related, with closer values being more strongly related than more distant ones (Tobler, 1970). Environmentally relevant variables often have strong spatial dependence, for example, haze pollution in city i will spread to neighboring city j with air flow, and haze in city j will in turn increase air pollution in city i, exhibiting geographical clustering with high-polluted area neighboring and low-polluted area neighboring. On the other hand, there is also spatial dependence on urban policies. For example, local government officials will imitate neighboring cities to make similar decisions, which are also understood as the congruence effect, and this phenomenon is not interrupted by provincial border boundaries, but decays with an increasing geographical radius (Deng and Zhao, 2018). Therefore, the spatial dependence of both explanatory and explanatory variables should be considered in the model, as reflected in the corresponding inclusion of spatial lagged terms of the explained and explanatory variables. We set Eq. 3 as a spatial panel equation.

$$\begin{aligned}
 \ln AP_{i,t} = & \beta_0 + \rho_1 W_{ij} \ln AP_{i,t} + \beta_1 \ln urban_{1,i,t} + \beta_2 W_{ij} \ln urban_{1,i,t} \\
 & + \alpha X_{i,t} + \gamma W_{ij} X_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t}
 \end{aligned}
 \tag{4}$$

Eq. 4 is a spatial panel Durbin model (SDM) with the spatial lagged terms of the explanatory variables and

explanatory variables, and the validity of the model setting in the next section will be checked. In the Eq. 4, W denotes the spatial weight matrix, which evaluates the dependence between the cities and their neighboring areas. Also, a geographic distance matrix is constructed to describe the dependence, that is, the closer the geographic distance, the closer the spatial weights of cities are to 1. The weight elements W_{ij} are as follows:

$$W_{ij} = \begin{cases} \frac{1}{d_{i,j}}, & i \neq j \\ 0, & i = j \end{cases}
 \tag{5}$$

where $d_{i,j}$ represents the geographical distance between city i and city j and calculated by their latitudes and longitudes.

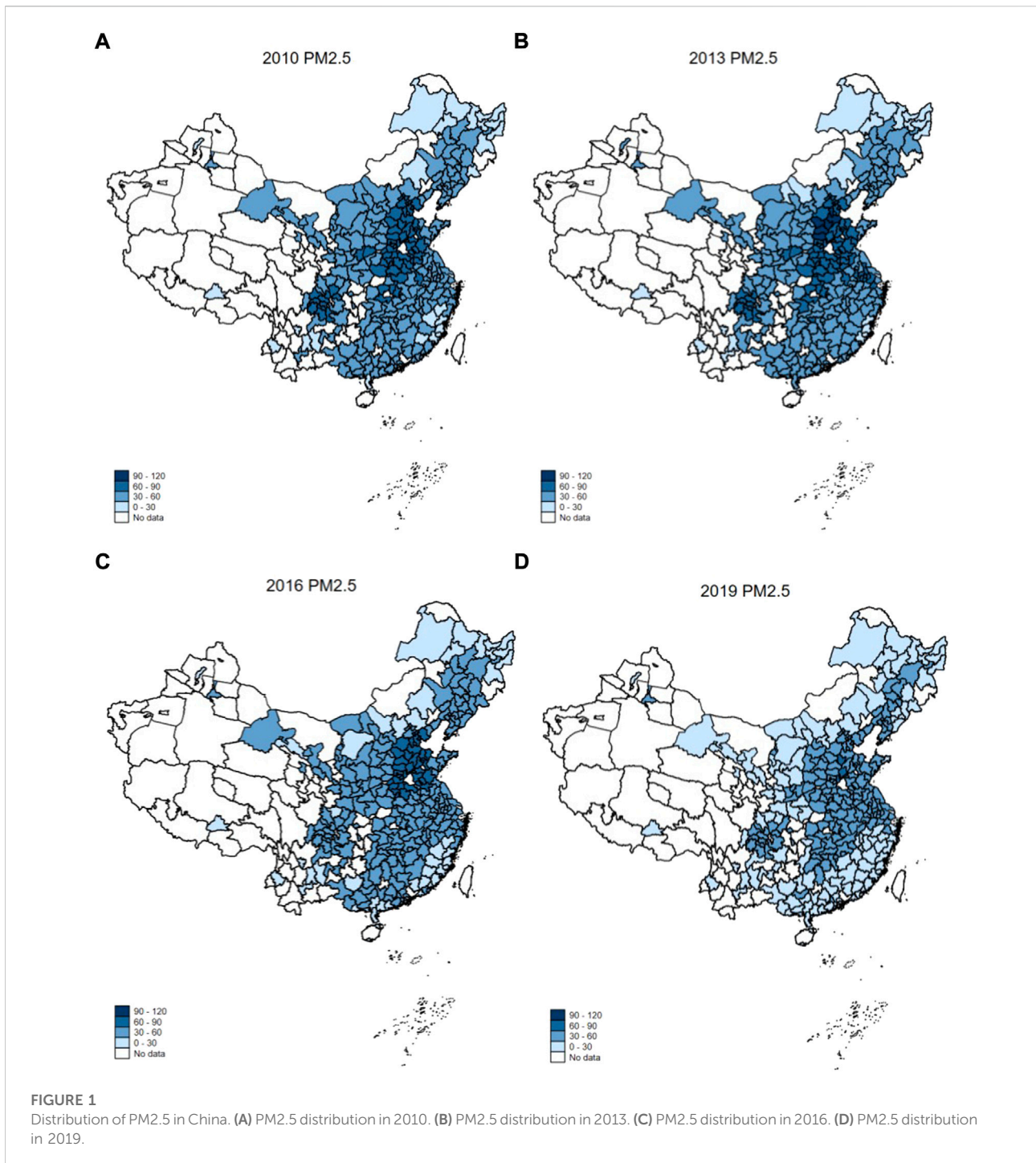
2.4 Spatial autocorrelation test and model identification

2.4.1 Spatial autocorrelation test

To test the spatial autocorrelation of air pollution, we use the Moran’s I index, which is given by

$$I = \frac{n}{\sum_{i=1}^n \sum_{j=1}^n W_{ij}} \cdot \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2},
 \tag{6}$$

where n denotes the number of cities, W_{ij} is the spatial weight matrix, and x is the annual average concentration of PM2.5. The Moran’s I describes the autocorrelation of the spatial distribution of variables in the range of [-1, 1]. When the Moran’s I is significantly greater than zero, there is a positive correlation of PM2.5 concentrations between cities, that is, high-pollution areas



are adjacent to high-pollution areas. However, if the Moran's I is significantly less than zero, there is a negative spatial correlation of high-pollution areas are adjacent to low pollution areas. The test results in Table 2 show that the Moran's I from 2010 to 2019 is positive at the 1% significance level, and the scatter plots in Figure 2 also represent the forms of spatial linkages between cities and their neighboring regions. Therefore, the spatial

dependence of air pollution exists among cities, it is reasonable to consider the spillover effect and choose the spatial econometric model.

2.4.2 Model identification

To determine the optimal spatial model for the sample data, we follow the method of Elhorst (2014) and identify the model

TABLE 2 Moran's I for PM2.5.

Variable	Year	Moran's I	Z	p value
PM2.5	2010	0.155	21.671***	0.000
	2011	0.136	19.128***	0.000
	2012	0.125	17.569***	0.000
	2013	0.134	18.873***	0.000
	2014	0.135	19.024***	0.000
	2015	0.166	23.082***	0.000
	2016	0.167	23.184***	0.000
	2017	0.137	19.437***	0.000
	2018	0.148	20.694***	0.000
	2019	0.150	21.060***	0.000

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

through a “general to specific” step, and the test results are shown in Table 3.

First, we test the spatial effects with the residuals of OLS regression of Eq. 3.

The results show that, for both spatial errors and spatial lags, LM and robust LM tests reject the original hypothesis that the model is not spatially correlated. In this situation, setting up a spatial Durbin model (SDM) is more robust (LeSage and Pace, 2009).

Second, we conducted a Hausman test to determine whether the fixed effect (FE) model or random effect (RE) model should be selected. With the null hypothesis H_0 : random effect is the preferred model, the chi-square statistic is 119.02, which rejects the H_0 at 1% significance level, so the fixed effect model should be used. In addition, considering that the data are collected from

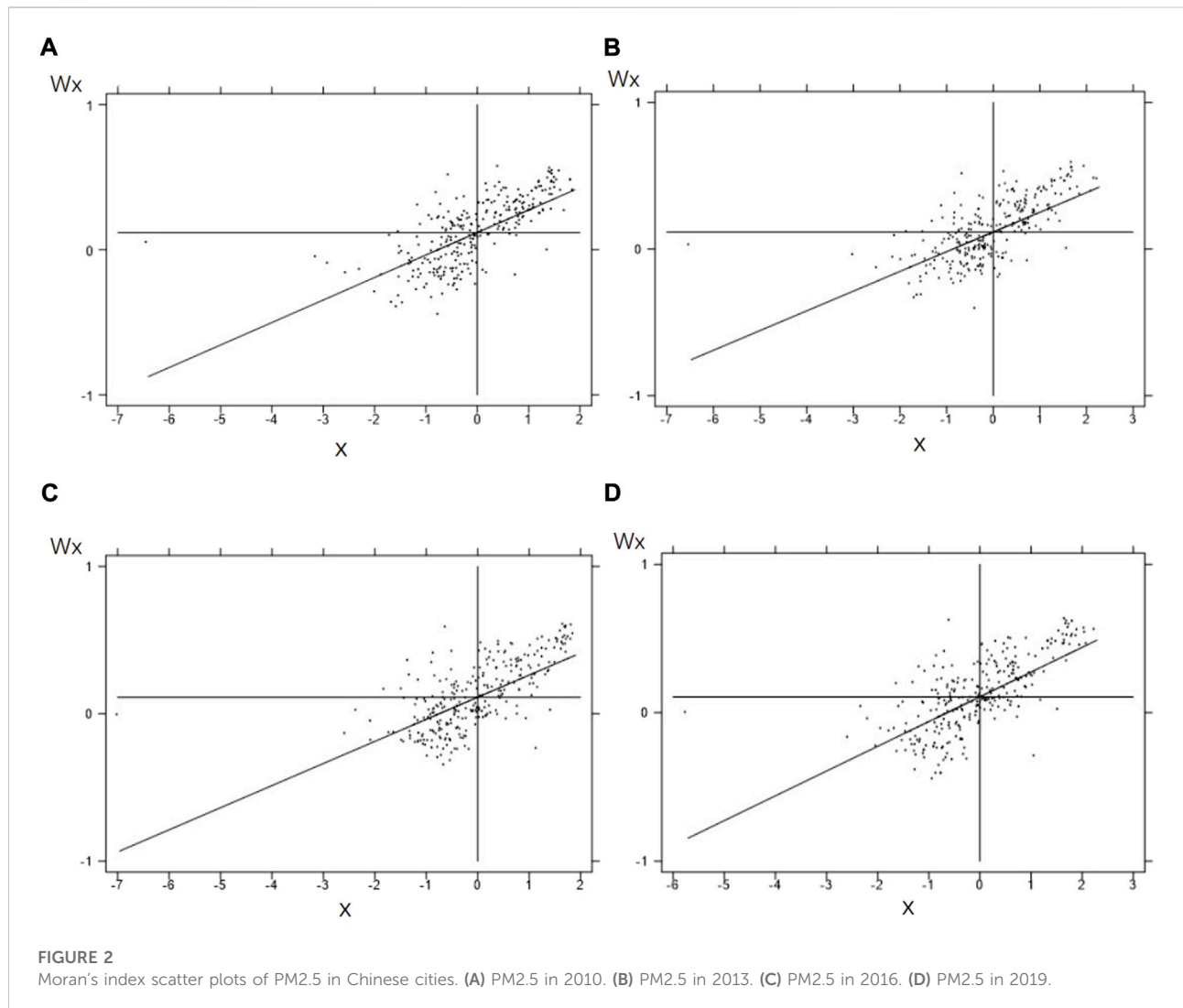


TABLE 3 Model inspection results.

Indicator test	Statistics	p value
Moran's I	79.743***	0.000
LM-lag	4,992.664***	0.000
LM-err	5,993.417***	0.000
R-LM-lag	350.790***	0.000
R-LM-err	1,351.543***	0.000
Wald test (SDM versus SAR)	217.21***	
Wald test (SDM versus SEM)	140.28***	

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

277 cities in 10 years, we believe it is necessary to control the heterogeneity between cities and years, so the fixed effect controller for both cities and years is the optimal choice, meanwhile, the LR test shows that the two-way fixed effect model outperforms either time or individual fixed effect model at 1% significance level.

Finally, we test whether the spatial Durbin model (SDM) could degenerate into a spatial error model (SEM) or a spatial lag model (SAR) (Elhorst, 2014). First, we test whether it can reduce into a spatial lag model (SAR). For the original hypothesis $H_0: \beta_2 = \gamma = 0$, the Wald test statistic is 217.21, which rejects the original hypothesis at 1% significance, so the SDM model cannot reduce into a SAR model; second, we test whether it can reduce into a spatial error model. For the original hypothesis $H_0: \gamma = -\rho_1\alpha$ and $\beta_2 = -\rho_1\beta_1$, the Wald test statistic is 140.28, which rejects the original hypothesis at 1% significance level, and the SDM model cannot reduce to the SEM model. In summary, the SDM model of model 4) is appropriate for our problem.

3 Model result and conclusion

3.1 Estimation results

The parameters estimators of the spatial Durbin model (SDM) and dynamic spatial Durbin model (SPDM) were obtained by the quasi-maximum likelihood method (QMLE) (Yu et al., 2008) and compared with those of the two-way fixed effects model (two-way FE) and the spatial autoregressive model (SAR). Many researchers argued that a special understanding of coefficients with spatial lag terms is needed (Anselin and Legallo 2006; Kelejian et al., 2006). LeSage and Pace. (2009) proposed that the average direct, indirect, and total effect are understood as marginal effects of explanatory variables when compared with the non-spatial model (Belotti et al., 2017). The calculation for the direct and indirect effects is given in the following equations:

Direct effect:

$$[(I - \rho W)^{-1}(\beta_{1k}I_N + \beta_{2k}W)]^d. \quad (7)$$

Indirect effect:

$$[(I - \rho W)^{-1}(\beta_{1k}I_N + \beta_{2k}W)]^{\overline{rsum}}, \quad (8)$$

where β_{1k} is the coefficient of the explanatory variables and β_{2k} is the coefficient of the spatial lag term of the explanatory variables; I is the unit matrix and \bar{d} denotes the mean of the diagonal elements of the matrix; and \overline{rsum} denotes the mean of the row sum of the non-diagonal elements of the matrix. We report the regression results of the three models in Table 4.

Table 4 presents the effects of urbanization on air pollution, with the estimated coefficients of spatial models listed in columns (1)–(9) and compares with the spatial models, and the estimation results of the fixed effect (FE) model are shown in column (10). In general, the addition of the spatial lag term in the model does not affect the sign of the core explanatory variables, but the magnitude of the estimated coefficients, that is, the non-spatial model will overestimate the impact of urbanization on air pollution. The spatial lagged terms of the explanatory variables (WlnAPs) are different from zero at the 1% significance level in all three spatial models, reflecting the spatial dependence of “high–high” and “low–low” agglomeration, which is also consistent with the pattern of haze distribution in Figure 1. The coefficient of WlnAP in SDM is 0.9690, which implies for every 1% increase in the average PM2.5 of neighboring cities, the PM2.5 of local cities increases by more than 0.97% net of other explanatory variables. However, the coefficients of SDM (0.9690) and SPDM (0.9624) are quite different from those of SAR (2.3714), we believe that the spatial lagged terms of the explanatory variables (e.g., WlnpGDP) help explain the spillover effects of air pollution from the neighboring cities. Different from the SAR model, which has the same proportion of direct and indirect effects, the SDM model is more flexible in describing spatial spillovers (Elhorst 2014). Meanwhile, the time lag term of the explained variable (LlnAP) is also significantly positive at 1% level, indicating that haze pollution is not only spatially dependent, but also time-dependent. Since the dynamic Durbin model provides more enriched information than other models, this study mainly focuses on the estimation results of it.

In terms of explanatory variables, the long-run direct effect in column (4) shows that the urbanization significantly inhibits air pollution, surprisingly; the indirect effects of urbanization are as strong as the direct effects, suggesting that urbanization can reduce air pollution in both local and surrounding cities. We believe the results derived from the following reasons: first, the urbanization level of regional central cities, such as Beijing, Shanghai, Wuhan, and Chengdu, is generally high. The siphon effects of the industry in those cities promote the merger and reorganization of small enterprises in the surrounding area and reduce unit pollution emissions through

TABLE 4 Model estimation results.

Explanatory variable	SDM			Dynamic_SDM			SAR			FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	LR_Direct	LR_Indirect	LR_Total	LR_Direct	LR_Indirect	LR_Total	LR_Direct	LR_Indirect	LR_Total	
ln Urban ₁	-0.0271*** (-5.03)	-0.8633* (-1.76)	-0.8903* (-1.80)	-0.0465*** (-6.94)	-0.0435*** (-6.29)	-0.0900*** (-6.77)	-0.0137*** (-3.42)	0.0230*** (3.39)	0.0093*** (3.33)	-0.0521*** (-8.21)
lnPGDP	0.0278** (0.217)	1.2451 (0.50)	1.2728 (0.51)	0.0346** (2.01)	0.2688 (1.57)	0.3034* (1.82)	0.0247*** (2.83)	-0.0414*** (-2.85)	-0.0167*** (-2.86)	0.0020* (1.92)
lnPop	0.0266*** (2.74)	4.2520* (1.71)	4.2786* (1.71)	0.0150*** (2.76)	0.3265*** (3.17)	0.3415*** (3.30)	0.0116*** (3.58)	-0.0194*** (-3.59)	-0.0078*** (-3.59)	0.0104** (2.38)
lnTrans	-0.0209** (-2.02)	-4.3869 (-1.61)	-4.4078 (-1.62)	-0.0073 (-1.36)	-0.4013*** (-3.89)	-0.4086*** (-3.95)	-0.0016 (-0.49)	0.0026 (0.49)	0.0011 (0.49)	-0.0118*** (-2.71)
lnFDI	0.0039** (2.18)	0.7571* (1.74)	0.7610* (1.75)	0.0019 (1.49)	0.0420* (1.89)	0.0439** (1.98)	0.0010 (1.36)	-0.0017 (-1.36)	-0.0007 (-1.36)	0.0020** (1.92)
lnSec	-0.0255 (-0.96)	-11.4666* (-1.72)	-11.4921* (-1.71)	0.0145 (0.87)	-0.6415* (-1.87)	-0.6270* (-1.82)	0.0236** (2.29)	-0.0396** (-2.29)	-0.0160** (-2.29)	0.0168 (1.52)
Green	-0.0209** (-2.02)	-4.3869 (-1.61)	-4.4078 (-1.62)	0.0445 (0.73)	0.0417 (0.72)	0.0861 (0.73)	-0.0016 (-0.49)	0.0026 (0.49)	0.0011 (0.49)	-0.0118*** (-2.71)
lnMetro	-0.0005** (-2.56)	-0.0786 (-1.56)	-0.0791 (-1.56)	-0.0001* (-1.87)	-0.0002 (-0.10)	-0.0004 (-0.17)	-0.0002*** (-4.12)	0.0003*** (4.13)	0.0001*** (4.12)	-0.0002 (-1.31)
WlnAP (ρ)		0.9690*** (99.65)			0.9624*** (82.68)			2.3714*** (80.29)		
LlnAP					0.3169*** (14.07)					
L.WlnAP					-0.6311*** (-6.06)					
Individual fixed		Y			Y			Y		Y
Time fixed		Y			Y			Y		Y
Control variable	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,770	2,770	2,770	2,770	2,770	2,770	2,770	2,770	2,770	2,770

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

the economy scale effect. Second, with the overall improvement of the regional urbanization level, cities change from individual development to an integrated regional development model led by urban agglomerations (Ruining et al., 2021), the resources can achieve higher allocation efficiency, which in turn improves the level of haze governance in the whole region (Zhang et al., 2020). Finally, due to the spatial spillover effects of urbanization, the increased level of urbanization in the surrounding area can drive the development of local urbanization, which in turn reduces local air pollution.

Regarding the control variables in Table 4, the direct and indirect effects of \ln PGDP are both positive, indicating that economic development still comes at the cost of environmental pollution. Similarly, the direct and indirect effects of \ln Pop are positive as well, due to the additional demand for transportation, housing, and resource consumption caused by population clustering, and the strong spatial correlation of China's population, that is, "dense in the east and sparse in the west," which makes the indirect effect of population significantly positive in the model.

The positive direct effect of FDI indicates that the introduction of foreign capital is still the cause of urban pollution in China and confirms the "Pollution Halo Hypothesis." FDI affects the host country's environment mainly through the scale, structural, and technical effects (Grossman and Krueger, 1995). The scale effect indicates that FDI will affect environmental pollution by expanding the scale of production, as well as on capital accumulation and taxation; the structural effect shows that FDI will affect the industrial structure of the investing country, because foreign companies are more competitive in technology and management, which will compress the survival of local companies; and the technology effect shows that the technology introduced into host country by FDI help reduce the pollution emissions. Developed countries with strict environmental regulations tend to develop clean industries and shift pollution-intensive industries to developing countries through foreign direct investment (Wang et al., 2020), and FDI in China has shown more scale and structural effects than technology effects which could compensate for the environmental pollution. The positive indirect effect of FDI in column (5) could result from a "learning effect" in regional policy decision (Du et al., 2022), cities with lenient environmental policies can attract more foreign investment and are more likely to achieve the target of political performance such as GDP.

The secondary industry (\ln Sec), mainly including energy supply and manufacturing, theoretically increases air pollution. However, the direct effects in columns (1) and (4) are insignificant. We argue that in the context of China's smallholder economy, agricultural production processes such as straw burning have caused serious air pollution, and the replacement of the secondary industry to the first industry

would not cause serious additional pollution. In addition, the Chinese government implemented an industrial transformation plan from labor-intensive industries to environmental friendly development during 2010–2019 and guided the industrial upgrading of enterprises through environmental policies, so the development of the secondary industry significantly reduced the haze pollution in the surrounding areas with a coefficient -0.6415 .

The direct effect of rail transit (metro) shows a positive impact on air quality by easing road congestion and reducing vehicle exhaust emissions. But the traffic infrastructures (\ln Trans) can also effectively alleviate local traffic congestion, and its indirect effect (-0.4013) is significantly different from the direct effect (-0.0073). On the one hand, a strong substitution relationship between roads and other transportation facilities, such as the replacement of the freight function of the surrounding urban road network with local high-quality transportation facilities, can reduce transportation time and cost, and thus reduce air pollution in the surrounding areas. On the other hand, local road infrastructure investments, investments with peer effects among cities, will drive similar investments in surrounding areas, and thus alleviate the traffic pressure in the region.

3.2 Robustness analysis

To verify the robustness of the model, we re-estimate the model using three methods, which include replacement of the explanatory variables, replacement of the core explanatory variables, and replacement of the spatial weight matrix.

3.2.1 Replacing the explained variable

In 2012, China's Ministry of Environmental Protection issued a new ambient air quality standard (GB3095-2012), using the air quality index (AQI) to describe the air quality of cities. The AQI is based on six atmospheric pollutants: sulfur dioxide, nitrogen dioxide, carbon monoxide, ozone, particulate matter with a particle size of 10 microns or less (PM10), and particulate matter with a particle size of 2.5 microns or less (PM2.5). Compared with PM2.5, the AQI can reflect urban air pollution more comprehensively. In addition, in September 2013, China's state council issued the Action Plan of Air Pollution Prevention and Control, followed by corresponding pollution control policies in various cities. In order to test the robustness of regression results under the policy shock, we used the sub-data from 2013 to 2019 and the annual average AQI index as the explained variable for the regression, as shown in Table 5 (1).

The coefficient of the $W\ln$ AQI is 0.918, which is close to the result of baseline regression, indicating that AQI has a similar spatial spillover effect and can be effectively used as a surrogate variable of urban air pollution. Urbanization, the core explanatory variable, still significantly reduces air pollution. Although the significance of some

TABLE 5 Regression results of replacing the interpreted variable.

Variables	(1)	(2)	(3)	(4)
	Replacing the explained variable lnAQI	Explanatory variable ln urban ₂	Explanatory variable ln urban ₃	Replace weight matrix W ₃
ln urban ₁	-0.0848 (-0.08)			-0.0490*** (-9.76)
ln urban ₂		-0.0546* (-1.76)		
ln urban ₃			-0.0367*** (-4.64)	
lnpGDP	-0.2744 (0.05)	0.0124 (0.98)	0.0249** (1.98)	0.0008 (0.08)
lnFDI	-0.0046 (-0.06)	0.0049* (1.81)	0.0042** (2.23)	0.0020** (2.09)
lnpop	0.0705 (0.05)	0.0169** (2.21)	0.0230*** (2.63)	0.0098** (2.09)
lnTrans	0.2705 (-0.04)	-0.0238** (-2.16)	-0.0221** (-2.05)	-0.0119*** (-3.04)
lnSec		-0.0375 (-0.88)	-0.0248 (-0.91)	
Green		0.2226 (1.57)	0.0000 (0.90)	
lnMetro		-0.0005** (-2.06)	-0.0005*** (-2.62)	
P	0.9253*** (31.26)	0.9695*** (101.05)	0.9692*** (100.04)	-0.1273*** (-3.51)
Control variable	Yes	Yes	Yes	Yes
Observations	1,662	2,770	2,770	2,770

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

control variables decreases due to the reduction of samples, the signs of regression coefficients are basically unchanged, which proves the robustness of the model.

3.2.2 Replacing the core explanatory variables

We use the population proportion and the urban expansion variable as alternative variables to the core explanatory variable ln urban₁, where ln urban₂ represents the urban population proportion and ln urban₃ represents the ratio of the non-zero nighttime light pixels to the total pixels of a city. The regression results are shown in columns (2) and (3) of Table 5. The signs and significance of explanatory variables keep robust.

3.2.3 Replacing the spatial weight matrix

We also constructed the nested matrix with geographical and economic factors for the robust test. Compared with the geographic distance matrix, the nested matrix takes the economic connection between cities into consideration. The matrix is constructed as follows:

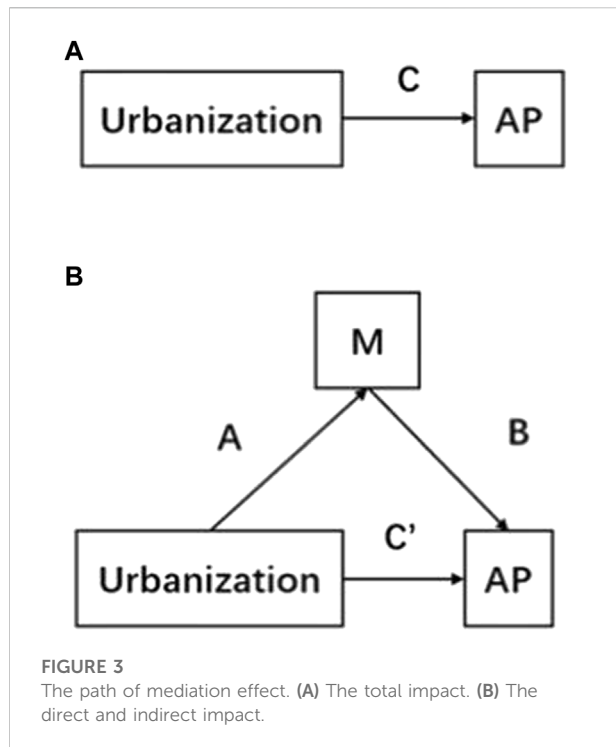
$$W_2 = \omega \cdot W_1 + (1 - \omega) \cdot W_3, \tag{9}$$

where W₃ is the economic distance matrix and W_{3ij} is the inverse of the absolute difference of per capita GDP between regions i and j. ω is the weight of matrix nested and is set as 0.5 (Shao, 2019). The results are shown in Table 5 column (4). The coefficients are robust except for the Wlnpm25 changes due to the change in the matrix.

TABLE 6 Regression results based on systematic GMM.

Variable	Coef	Z
L.lnPM2.5	0.1541***	20.86
ln urban ₁	-0.0343***	-10.10
lnpGDP	0.0258***	3.88
lnFDI	0.0055***	12.82
lnpop	0.0546***	10.97
lnTrans	-0.0031	-0.81
lnSec	-0.1259***	-12.34
Green	0.0527	1.34
Metro	0.0000	0.30
W · lnPM2.5	1.3449***	68.22
W · ln urban ₁	0.0571***	8.69
W · lnpGDP	-0.0435***	-2.18
W · lnFDI	-0.0175***	-5.53
W · lnpop	0.1026***	7.57
W · lnTrans	0.0629***	4.04
W · lnSec	-7.033***	-21.72
W · Green	-0.3491	-1.43
W · Metro	0.0011***	2.76
Test statistics	Statistics	p value
Sargan test	272.0520	0.67
AR (1) test	-8.23	0.00
AR (2) test	1.24	0.21

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



3.4 Endogeneity analysis

The spatial dynamic Durbin model (SPDM) can solve the endogeneity problem caused by the spatial lagged term of the explanatory variable, the temporal lagged term of the explanatory variable, and the omission of explanatory variables during the model setting. In addition, nighttime lighting data (NTL) selected as a proxy variable for urbanization also ensure the exogeneity of the core explanatory variables. However, the endogeneity arising from the interplay between explanatory and explained variables still cannot be ruled out. In fact, not only urbanization affects air pollution, but air pollution may also affect urbanization in turn (Gan et al., 2020). Therefore, we use the first-order time-lagged terms of the explanatory and core explanatory variables as instrumental variables (Han and Yang, 2020; Wang et al., 2022) of a systematic GMM approach (Lee and Yu 2014) and choose the population growth rate (Shao et al., 2019) as an instrumental variable of urbanization to estimate the model, and the results are shown in Table 6.

The regression results in Table 6 show that the p value of Arellano–Bond AR (1) is less than 0.1, and that of AR (2) is greater than 0.1, indicating that there is no second-order autocorrelation in the series. The p value of the Sargon over-identification test is greater than 0.1, rejecting the original hypothesis that the instrumental variables are invalid. Therefore, the regression results in Table 6 are considered convincing. The estimation coefficients of urbanization are

still significantly negative after excluding the endogeneity of mutually causal. The regression results of other explanatory variables remain basically unchanged, confirming the conclusion that urbanization attenuates air pollution.

3.5 Analysis of the mediation effect

In order to explore the mechanism that urbanization inhibits air pollution, we intend to test whether the industrial structure upgrading (ISU) and energy consumption structure (ECS) can act as the mediator variable between urbanization and air pollution, following the approach of Jin et al. (2022) and Yu (2022). We follow the causal steps proposed by Baron and Kenny (1986), which are generally adopted when setting the mediation models. The steps are shown in Figures 3A,B.

In Figure 3A, C is the path which shows that urbanization influences air pollution. Since the mediator is not involved, C represents the total impact. Figure 3B shows the relationship between urbanization and air pollution after controlling the mediator variable. Also, path A represents the impact of urbanization on the mediator, path B represents the impact of the mediator on air pollution, and both A and B form the indirect impact. The path C' represents the direct impact of urbanization on air pollution after controlling the mediator variable. Therefore, total impact (C) = indirect impact (AB) + direct impact (C'). To test the existence of indirect impact (AB), the following models are constructed:

$$\ln PM2.5 = \theta_0 + \beta_0 \ln Urban + \varphi X + \varepsilon, \quad (10)$$

$$M = \theta_1 + \beta_1 \ln Urban + \varphi X + \mu, \quad (11)$$

$$\ln PM2.5 = \theta_2 + \beta_2 \ln Urban + \gamma_1 M + \varphi X + \tau \quad (12)$$

We use the dynamic spatial Durbin model (SPDM) to estimate Eqs. 10–12, and the direct effects are calculated for each equation referred to Eq. 7. Coefficients $\beta_0, \beta_1, \beta_2$ are significant, and after adding the intermediary variable M, β_2 compared with β_0 is significantly smaller, indicating a mediating effect. The estimation results in Table 7 show that both ISU and ECS have mediation effects, and we consider their mechanisms as described below:

For industrial structure upgrading (ISU), the Petty–Clark theorem (Clark 1940) points out that urbanization and industrialization proceed simultaneously: the labor force first transfers from the primary industry to the secondary industry, then to the tertiary industry. In China's Urbanization process, a large number of rural surplus labor forces with lower marginal productivity to enter the urban industrial sector with higher productivity, and in later stages, the tertiary industry replaces the secondary to become the leading industry, which is more environmentally friendly than the secondary industry. Moreover, the upgrading of the industrial structure will promote the large-scale and intensive use of energy at the

TABLE 7 Analysis of the mediating effect.

Variable	Total effect C	Indirect effect A	Direct effect C'	Indirect effect A	Direct effect C'
	M = ISU			M = ECS	
lnUrban	-0.0465*** (-6.94)	0.0411*** (6.61)	-0.0240*** (-4.50)	0.0146*** (2.26)	-0.0447*** (-6.30)
Mediator variables			-0.0787** (-1.95)		-0.0858** (-1.93)
Observations	2,720	2,720	2,720	2,720	2,720

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

TABLE 8 Heterogeneity analysis.

Variable	Eastern	Central section	Western	Eastern	Central section	Western
	(1)	(2)	(3)	(4)	(5)	(6)
$W \cdot \ln PM_{2.5}$	0.906*** (32.81)	0.931*** (43.82)	0.763*** (11.53)	0.906*** (32.66)	0.929*** (42.48)	0.759*** (11.36)
$\ln \text{urban}_1$	0.015 (1.17)	0.034*** (3.07)	-0.033** (-2.00)	0.013 (1.00)	0.048*** (4.04)	-0.028* (-1.65)
$\ln^2 (\text{urban}_2)$	0.057 (1.49)	0.024* (1.82)	-0.003 (-1.19)	0.008*** (4.39)	0.014*** (8.32)	-0.003 (-1.33)
$W \cdot \ln \text{urban}_1$	0.080** (2.09)	-0.078*** (-2.94)	-0.017 (-0.58)	0.064* (1.66)	-0.066*** (-2.59)	-0.023 (-0.80)
$\ln GDP$	-0.001 (-0.06)	0.004 (0.26)	-0.013 (-0.47)	1.673 (0.73)	4.501* (1.90)	9.189*** (3.33)
$\ln^2 (GDP)$				-0.142 (-0.68)	-0.383* (-1.70)	-0.908*** (-3.42)
$\ln^3 (GDP)$				0.004 (0.63)	0.011 (1.51)	0.030*** (3.50)
Lnsecond	-0.012 (-0.60)	0.028** (2.05)	0.031 (1.44)	-0.011 (-0.54)	0.028* (1.32)	0.028 (1.32)
Control variable	Y	Y	Y	Y	Y	Y
Observations	1,080	1,110	570	1,080	1,110	570
R-squared	0.197	0.208	0.154	0.196	0.278	0.153

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

macro level and lead to innovations in production technologies at the micro level, thereby reducing air pollution in energy consumption and production processes.

For the energy consumption structure (ESC), we believe that on the one hand, urbanization can change residents' energy consumption habits, reduce the use of highly polluting energy such as coal, and increase the use of clean energy such as natural gas and solar energy. On the other hand, urbanization enhances the efficiency of energy use. For example, the government could set up industrial zones to conduct unified supervision over energy-intensive enterprises around the city, so as to improve energy utilization efficiency and pollution treatment efficiency, and thus reduce pollution.

3.6 Regional heterogeneity

Urbanization reduced air pollution nationwide, but there is regional variability in the degree of urbanization, for example, urbanization is significantly greater in the east

and central regions than that in the west, we are interested in regional variability in the impact of urbanization on air quality in China, so we divided the sample into three groups: central, eastern, and western for heterogeneity analysis, and the regression result as shown in Table 8.

From the first row of Table 8, $W \ln PM_{2.5}$ is significant at 1%, the spillover effect of air pollution in the western region is weaker than that in the other region. The reasons for this could be twofold: first, the mountains and basins in the west impede air flow and haze dispersion; second, the lack of large-scale industrial clusters in the west makes regional aggregation of pollution less frequent, which weakens the spatial dependence of the haze.

In order to test the nonlinear relationship between air pollution and urbanization, we add the quadratic $\ln (\text{urban}_1)^2$ and tertiary $\ln (\text{urban}_1)^3$ terms of the urbanization variable in the regressions. From the columns (2), (4), and (5) in Table 6, the coefficients of the quadratic terms are significantly different from zero in both eastern and central regions, indicating the nonlinear relationship between urbanization and air pollution in these two

regions. The coefficients of both primary and secondary terms are significantly positive in the central cities, indicating that urbanization accelerates the rate of air pollution. Compared with the coefficient of the industrial structure ($\ln\text{Sec}$) in eastern cities (-0.012), the sign of $\ln\text{Sec}$ in central cities is positive (0.028), which indicates the industrial scale effect of central cities is offset by other factors during the urbanization process. In column (6), the coefficient of $\ln\text{Urban1}$ in western cities is negative (-0.028) at 10% significance, while the coefficient of the secondary term is insignificant, and the nonlinear relationship is difficult to determine.

Referring to the environmental EKC hypothesis, we are also interested in the relationship between the economic growth and air quality, so we add the quadratic and tertiary terms of $\ln\text{pGDP}$ in columns (4), (5), and (6). The regression results confirm the existence of a nonlinear relationship between GDP and air pollution. In columns 5) and (6), the primary term is positive and the secondary term is negative in both the central and western cities, and the tertiary term is significantly positive in the western cities, which is consistent with the “N-shaped” curve of the EKC hypothesis, the coefficient in the western cities indicates that the economic growth of the western cities still depends on the high-pollution industries. Although the haze pollution in the eastern cities is not significant, but the coefficient of $\ln\text{Sec}$ (-0.01) is negative, we believe that in the eastern region, “environmentally friendly” investment and intensive green industrial development have reduced the pressure of economic growth on air quality.

4 Conclusion and discussion

4.1 Research conclusion

Based on the panel data of 277 prefecture-level cities in China from 2010 to 2019, we use the spatial panel Durbin model (SDM) to analyze the mechanism and regional heterogeneity of urbanization on air pollution and choose PM_{2.5} land lights (NTL) as the core explained and explanatory variables. The main conclusions are as follows:

- (1) During the time span of the sample, the urbanization had a significant improvement in air quality. The air quality will be improved by 0.028% with every 1% improvement in urbanization. This conclusion is still valid under a series of robust tests.
- (2) Population and traffic are two major factors that affect air quality in the process of urbanization. The increase in the population density worsens the air quality, and every 1% increase in the population density causes the air quality to decline by 0.019%. The improvement of traffic can significantly affect the air quality. Every 1% optimization of the traffic road variable ($\ln\text{road}$) can cause the haze to decline by 0.021%. The rail transit variable (metro) has left a deep impression on us. Although only 38 cities have opened rail transit by 2019, the coefficient of metro is significant in all samples, and the rail transit plays an important role in improving air quality by alleviating urban congestion.
- (3) Industrial structure upgrading (ISU) has a mediating effect on urbanization and air pollution. Urbanization not only induces the changes in resident demand, but also upgrades the industrial structure during the demand adjustment. Additionally, ISU helps in optimizing production, adjusting the ratio of resource allocation, and reducing the input of high-carbon material such as coal and oil. Moreover, there are obvious differences between the energy demand and consumption in primary, secondary, and tertiary sectors. The upgrade of the industrial structure will reduce the proportion of primary sectors including mining and agriculture, increase the proportion of the tertiary sector, directly reduce the rigid demand for energy in production, and control the rapid growth of energy consumption. In addition, by optimizing resource allocation, the upgrading of the industrial structure can speed up the transfer of economic factors to high-productivity sectors like high-tech industry, promoting the coordinated development of various industries, and promote green and high-quality economic development, and thus reduce air pollution.
- (4) From the perspective of regional heterogeneity, the influence mechanism of urbanization in eastern, central, and western China is different. Due to the deepening and high-quality development, there is a tendency of “decoupling” between urbanization and air pollution in the eastern region. In the central and western regions, there is a nonlinear relationship between urbanization and air pollution. The regression results of GDP per capita, economic growth in the central region worsens air quality, but the quadratic coefficient $\ln^2(\text{GDP})$ is negative, which indicates that the trend is gradually decreasing. The first-order and second-order coefficients of urbanization variable $\ln\text{urban}_1$, $\ln^2(\text{urban}_2)$ are positive, indicating that urbanization is accelerating the deterioration of air quality. We believe that the impact of industrial expansion, traffic congestion, and increased resource consumption brought by urbanization in central China is greater than that of industrial upgrading and policy improvement. At present, the economic development in the western region is still at the cost of sacrificing the environment. However, as the western stage is still in the initial stage of development, it has not reached the threshold of environmental carrying capacity. As a result, the policy, financial support, and initial scale effect of the industry brought by urbanization can improve the air quality of cities, resulting in the phenomenon that the air quality in the western region improves with urbanization.

4.2 Discussion

The empirical results of this paper indicate that urbanization reduces air pollution; however, there are still shortcomings in the study process that limit the reliability of the conclusion. In order to describe the spatial interaction effect, we built a spatial weight matrix based on the geographical distance. However, we use an inverse distance matrix to focus on describing the geographical relationship between cities, while ignoring the economic and social links between cities. As a result, it is difficult to estimate the spillover effects of variables related to economic policies, which needs to be improved in our next work. In general, the use of dynamic panels can effectively overcome the endogeneity problem of missing important explanatory variables, but considering the availability of data, it is difficult to select panel data with a longer time span, resulting in insignificant dynamic panel estimating results. For further research, it is necessary to find variable groups with a time span. From the whole sample of this paper, urbanization has significantly improved the air pollution, but from the regional sample, except that urbanization in the west can significantly reduce haze pollution, urbanization in the middle is still positively related to haze pollution, while urbanization in the east is not significantly related to haze pollution. The reason for such unexpected phenomenon is that when conducting regional heterogeneity analysis, spatial dependence among cities in different regions will be ignored, and there are many more adjacent cities in the eastern and central regions than those in western regions, thus causing an underestimation of the spillover effect of central and eastern cities.

From the analysis of the mediating effect, we believe that high-quality urbanization is the fundamental way to avoid economic growth constrained by air pollution. As the central region has undertaken some heavy pollution industries in the eastern region, it has shown the trend of the environment for the economy in recent years. It should be corrected by encouraging scientific and technological innovation and strengthening policy guidance. The western region is in the primary stage of urbanization, so we should improve the development orientation in a timely manner, such as controlling the development of resource industries in a moderate manner, promoting tourism, big data, and other environment-friendly industries, and reducing dependence on heavily polluting

development approaches. Eastern cities should continue to improve transport infrastructure, increase R&D investment to alleviate air pollution caused by population aggregation, and better utilize the positive externality of the urban agglomeration effect to achieve sustainable development (Belotti et al., 2017; China Energy Statistical Yearbook, 2022; Gan et al., 2020; BNDT, 2022; Stats Gov, 2022).

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

SY (2nd author), LZ, MZ, and SY (4th author) designed the research; LZ, SZ, SY (4th author), and BZ collected the data; LZ and SY (4th author) contributed to data processing and analysis; LZ, SZ, SY (4th author), and BZ prepared the original draft; SY (2nd author), LZ, and MZ edited and reviewed the manuscript; and LZ contributed to the discussion. All authors have read and agreed to the published version of the manuscript. SY (2nd author): Shibing You, SY (4th author): Shuaixiang Yi.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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