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Research Article

Impacts of Urban Shrinkage on Haze Pollution-Evidence from China

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This study focuses on 55 shrinking cities selected by the urban shrinkage index using data about the urban population of 250 prefecture-level Chinese cities from 2012 to 2017. It analyzes the theoretical impacts of urban shrinkage on haze pollution and the spatial distribution and autocorrelation of urban shrinkage. The spatial error model (SEM) and the fully modified least squares (FMOLSs) regression are used to empirically examine the impacts of urban shrinkage on haze pollution at national and regional levels. The results indicate that shrinking cities showed spatial agglomeration and that northeast China had the largest number of shrinking cities. Nationwide, urban shrinkage reduced haze pollution. An increase in the proportion of secondary industries, economic development, and built-up areas intensified haze pollution, while an increase in the green area in parks alleviated such pollution. Regionally, except for west China, the impacts of urban shrinkage on haze pollution were significantly negative. Urban shrinkage in central China had the greatest impacts on haze, followed by northeast China and east China. Haze pollution was intensified by the increase in the proportion of secondary industries in east, central and west China, alleviated by economic development in east and west China, slowed down by the increase in green area in parks in northeast, east and west China, and aggravated by the rise in built-up areas in northeast, central, and west China. Targeted suggestions are proposed herein to reduce haze pollution, adapt to urban shrinkage and build quality small cities based on local conditions.

1. Introduction

China witnessed rapid urbanization and had an urbanization rate of a permanent population of over 60% at the end of 2020. The increasing urban population has led to environmental pollution issues such as haze pollution. New-type urbanization proposed in 2020 highlights promoting human-centered high-quality urbanization. It points out that efforts should be made to coordinate the cultivation of emerging cities and the improvement of shrinking cities, steadily reduce the area of shrinking cities, and adjust shrinking counties (cities) after conducting the prudent survey. Chinese cities face severe haze pollution at present. Will urban shrinkage slow it down? The answer to this question has important practical significance for building a beautiful China and meeting people's growing needs for a better life [1].

2. Literature Review

In 1988, German scholars Häußermann and Siebel first proposed the term "shrinking city" to describe massive population loss and hollowing out of cities [2]. In recent years, China also has shrinking cities [3]. Urban shrinkage is receiving growing attention from academia and government departments at home and abroad.

Existing research studies on urban shrinkage focus on the definition of related concepts [4–7], its driving mechanism [8–14] and countermeasures [15–17]. There are also studies on its impacts. The intuitive manifestation of urban shrinkage is population loss, but the essence is the loss of essentials like capital. Population loss results in idle houses and abandoned buildings, while capital loss leads to the economic downturn and unemployment [18]. Urban shrinkage also means loss of knowledge, technology, and innovation [19], reduces the vitality of cities and lowers residents' quality of life [20]. One of its positive impacts is that extra open space allows ecological reconstruction and is good for expanding green space and boosting urban biodiversity [21].

Some literature discusses the impacts of urban shrinkage on carbon emissions. For example, Liu et al. analyzed the CO_2 emissions of residents in shrinking prefecture-level cities based on data in 2005, 2010, and 2015. They found that urban shrinkage was positively correlated with the CO_2 emissions and that the energy efficiency of shrinking cities is lower than that of expanding cities of the same size [22]. Xiao et al. compared the long-term CO_2 emission of shrinking cities and expanding cities with 55 sample cities in northeast China and the Yangtze River Delta. They found that CO_2 emissions continued to grow in rapidly shrinking urban agglomerations and that CO_2 emissions fell in urban agglomerations undergoing mild and moderate shrinkage along with the decline of secondary industries [23].

Previous research studies have laid the foundation for this study but have some shortcomings. First, there were few discussions on the impacts of urban shrinkage on air pollution, and even fewer on its impacts on haze pollution. Second, a theoretical analysis of the impacts of urban shrinkage on haze pollution was absent. Third, there was no empirical research on the impacts of urban shrinkage on haze pollution.

This study makes up for the above-mentioned shortcomings. First, it puts urban shrinkage and haze pollution in the same framework to explore the positive and negative effects of urban shrinkage on haze pollution theoretically. Second, it empirically examines the impacts of urban shrinkage on haze pollution at national and regional levels. Thirdly, SEM and FMOLS are used to investigate the impacts of urban shrinkage on haze pollution.

3. Theoretical Analysis, Research Method and Model

3.1. Theoretical Analysis

3.1.1. Positive Impacts of Urban Shrinkage on Haze Pollution

Population loss impairs residents' demand for consumption (including energy consumption) and housing, thereby reducing constructions. Besides, relocation of companies to other cities not only reduces the consumption of fossil energy such as coal and oil but also decreases the demand for buildings like factories. Energy consumption leads to emissions of particulate matters and sulfur dioxide (SO_2), which directly aggravates haze pollution. Dust produced in constructions is the main contributor to PM_{10} [24]. Therefore, urban shrinkage reduces environmental pollution through reduced energy consumption and constructions. During urban shrinkage, trees on vacant land can regulate the climate, improve air quality and the ecosystem and reduce haze pollution [1].

3.1.2. Negative Impacts of Urban Shrinkage on Haze Pollution.

In the process of urban shrinkage, the young, and middle-aged migrate to other places. This increases the proportion of the elderly, who have limited knowledge and weak awareness of environmental protection, and their lifestyle is not environmentally friendly. Besides, they are more sensitive to price when buying products. The price of energy-saving and environment-friendly products is higher than ordinary ones, so they are reluctant to buy them, which is not conducive to improving air quality. Population loss stands for loss of knowledge and technology, which counts against technological progress and industrial transformation and upgrading. Company relocation to other cities reduces productivity, employee population, and tax revenue, which are bad for controlling urban haze pollution [1].

3.2. Method

3.2.1. Spatial Autocorrelation

(1) Global Spatial Autocorrelation

Global spatial autocorrelation was analyzed with Global Moran's I index [25]. The formula is

$$\text{Moran}'s\, I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}. \tag{1}$$

$S^2 = 1/n\sum_{i=1}^{n}(x_i - \overline{x})^2$ is the variance of observations, and $\overline{x} = 1/n\sum_{i=1}^{n} x_i$ the average value of all spatial unit observations. x_i and x_j represent observation values of the i-th and j-th spatial unit, n is the total number of spatial units, and w_{ij} is the spatial weight matrix. This paper employs the spatial adjacency weight matrix, whose set-up principle is

$$w_{ij} = \begin{cases} 1, & i \text{ and } j \text{ are adjacent}, \\ 0, & i = j, \text{ or } i \text{ and } j \text{ are not adjacent}. \end{cases} \tag{2}$$

(2) Local Spatial Autocorrelation

Local spatial autocorrelation was analyzed with local Moran's I index:

$$\text{Moran}'s\, I = \frac{\left(x_i - \overline{x}\right)\sum_{j=1}^{n} w_{ij}\left(x_j - \overline{x}\right)}{S^2}. \tag{3}$$

Its meaning of x_i, x_j, n and principle of w_{ij} set-up are the same as that of formula (1).

The correlation indexes of local spatial autocorrelation are divided into HH (high-high), HL (high-low), LH (low-high), and LL (low-low). If a local Moran's I index is positive, it indicates that there is a positive spatial autocorrelation between the haze pollution of spatial units in a certain province and its neighboring provinces, which belong to HH or LL type agglomeration. If a local Moran's I index is negative, it indicates that there is a negative spatial autocorrelation between the haze pollution of a spatial unit in a certain province and its neighboring provinces, which belongs to LH or HL type of agglomeration [1].

The relationship between Global Moran's I index and Local Moran's I index is

$$\sum_{i=1}^{n} \text{Local Moran}'s\, I = n \times \text{Moran}'s\, I. \tag{4}$$

3.2.2. Spatial Econometric Models. Spatial econometric models were divided into a spatial lag model (SLM), SEM, etc., [26].

The SLM is

$$Y = \rho WY + X\beta + \varepsilon. \tag{5}$$

Y is the explained variable, X is the explanatory variable matrix, W is the spatial weight matrix, and WY is the spatial lag explained variable. ρ means the spatial autoregressive coefficient that reflects the spatial dependence of the observed value of the sample, β the coefficient of the explanatory variable, and ε the random error term that obeys a normal distribution.

The SEM is

$$\begin{aligned} Y &= X\beta + \varepsilon, \\ \varepsilon &= \lambda W\varepsilon + \mu. \end{aligned} \tag{6}$$

μ is the independent and identically distributed residual, and λ the spatial autoregressive coefficient that reflects the influence of residuals in adjacent areas on residuals in this area.

3.3. Model Set-Up. To empirically test the impacts of urban shrinkage on haze pollution, the following econometric model was built:

$$\begin{aligned} \ln PM_{2.5} = {} & \beta_0 + \beta_1 \ln US + \beta_2 \ln SE \\ & + \beta_3 \ln GDP + \beta_4 \ln PGA + \beta_5 \ln LAND + \varepsilon_i. \end{aligned} \tag{7}$$

In Formula (7), $PM_{2.5}$ represents the annual average concentration of $PM_{2.5}$, namely haze pollution (unit: μg/m^3). *US* refers to urban shrinkage, *SE* to the proportion of secondary industries (unit: %), and *GDP* to the GDP per capita (2006 as the base period, unit: CNY/person). *PGA* represents the per capita green area in parks (unit: m^2), *LAND* the area of built-up areas (unit: km^2), and β_0 the constant term. Since natural logarithms of all variables are adopted, β_1, β_2, β_3, β_4 and β_5 are elastic coefficients to be estimated, and ε_i is the random error term.

3.4. Urban Shrinkage. Both the single index method [27, 28] and multiple index method [29] can measure urban shrinkage. This study draws on Xiao et al. [23] to measure urban shrinkage with the following formula:

$$US_{(t_0,t_1)} = t_1 - t_0\sqrt{\frac{P_{t_1}}{P_{t_0}}}. \tag{8}$$

$US_{(t0,\, t1)}$ means the population index between year t_0 and t_1. P_{t0} and P_{t1} are urban population in t_0 and t_1. The *US* change interval is $[0, +\infty)$. If US > 1, there was a population expansion. Otherwise, there was a population shrinkage.

3.5. Data Source. We analyzed data about 250 prefecture-level cities from 2012 to 2017, whose shrinkage indexes were calculated with formula (8). Among them, 55 cities had a shrinkage index of less than 1, which are research objects in this study. Data about $PM_{2.5}$ concentration come from the $PM_{2.5}$ concentration ranking of Chinese cities released by Greenpeace, an independent campaigning organization, on January 10, 2018. The proportion of secondary industries and per capita GDP are from *China City Statistical Yearbook* (2008–2018). GDP per capita come from *China Statistical Yearbook 2018*. Urban population, per capita green area in parks and built-up areas are from *China Urban Construction Statistical Yearbook* (2007–2017). Missing data have been filled in by interpolation. The 55 cities are divided into northeast, east, central, and west China, which include 21 cities in northeast China (Heihe, Yichun, Hegang, Jiamusi, Jixi, Mudanjiang, Baicheng, Jilin, Siping, Liaoyuan, Baishan, Tonghua, Fushun, Shenyang, Fuxin, Chaoyang, Benxi, Liaoyang, Anshan, Yingkou, and Dandong), 9 cities in east China (Zhangjiakou, Tangshan, Baoding, Cangzhou, Hengshui, Xingtai, Handan, Huai'an, and Langfang), 10 cities in central China (Datong, Taiyuan, Ma'anshan, Tongling, Zhangjiajie, Jingdezhen, Yiyang, Changsha, Shaoyang, and Chuzhou), and 15 cities in west China (Tongliao, Chifeng, Baotou, Jinchang, Yinchuan, Zhongwei, Pingliang, Suining, Guang'an, Zigong, Panzhihua, Lijiang, Anshun, Hezhou, and Shizuishan).

Descriptive statistics of the cities are shown in Table 1.

4. Empirical Research

4.1. Spatial Distribution of Shrinking Chinese Cities. Based on the 55 cities' shrinkage indexes, their spatial distribution was produced using ArcGIS 10.2 and Jenks Natural Breaks Classification system, as shown in Figure 1. The urban shrinkage indexes were divided into five grades from small to large. There were 6 grade-1 cities (with small urban shrinkage indexes) in Jilin and Hebei; 4 grade-2 cities, with 1 in Jilin and 3 in Hebei; 3 grade-3 cities, with 1 in Jilin and 2 in Hebei; 9 grade-4 cities, with 4 in the northeast, 3 in the west and 2 in the central; 33 grade-5 cities, with 12 in the

Table 1: Descriptive statistics of variables.

Variable	$PM_{2.5}$	US	SE	GDP	PGA	LAND
Mean	45.6490	0.9330	43.1160	25017.07	14.4196	93.9878
Median	42.9000	0.9838	42.0400	22248.93	13.2300	76.5000
Max	86.1000	0.9997	65.7200	64951.00	26.6200	553.0000
Min	14.8000	0.6484	13.8500	8553.899	7.5800	8.7100
Std. Dev.	15.3187	0.1048	11.8082	12964.24	4.5315	95.8217
Sum	2510.700	51.3171	2371.380	1375939.	793.080	5169.330
Observations	55	55	55	55	55	55

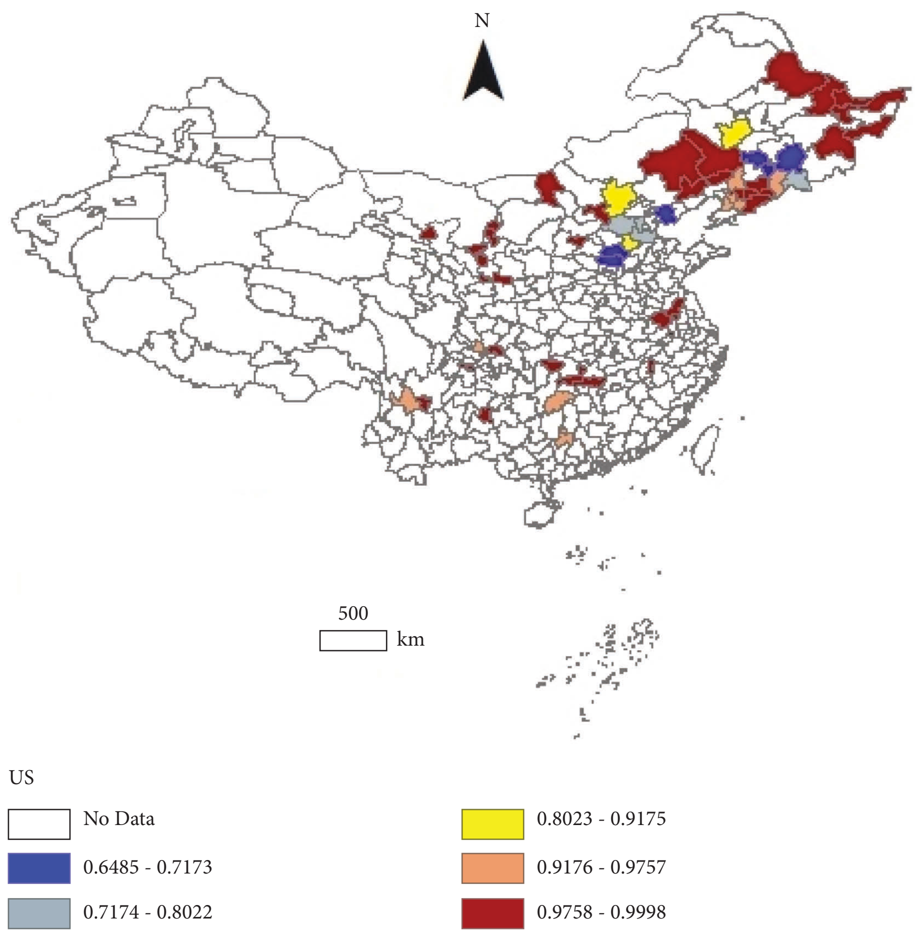

Figure 1: Spatial distribution of urban shrinkage in China.

northeast, 1 city in the east, 12 in the west and 8 in the central. To sum up, northeast China had the largest number of shrinking cities.

4.2. Spatial Autocorrelation of Shrinking Chinese Cities. Analysis with GEODA 0.9.5-*i* following queen adjacency revealed that Moran's I index of shrinking Chinese cities in 2017 was 0.5381. Monte Carlo randomization tests were conducted for 999 times, whose P value was 0.0010. This means shrinking cities showed spatial agglomeration in 2017.

The local spatial autocorrelation of urban shrinkage was examined with Moran's I scatter plot, as presented in Figure 2, where the horizontal axis indicates urban shrinkage, and the vertical axis indicates lagged urban shrinkage. 50 cities are located in the first or third quadrants, accounting for as high as 90.9%. This means there was an obvious agglomeration of shrinking cities. Only 5 cities are in the second and fourth quadrants, taking up 9.09%. Among them, 1 is located in the second quadrant, which means LH agglomeration, and 4 are located in the fourth quadrant, that is, HL agglomeration [1].

4.3. Empirical Research on the Impacts of Urban Shrinkage on Haze Pollution

4.3.1. Multicollinearity Test. Pearson correlation test was conducted to check the correlation between variables, the results of which are presented in Table 2. All correlation

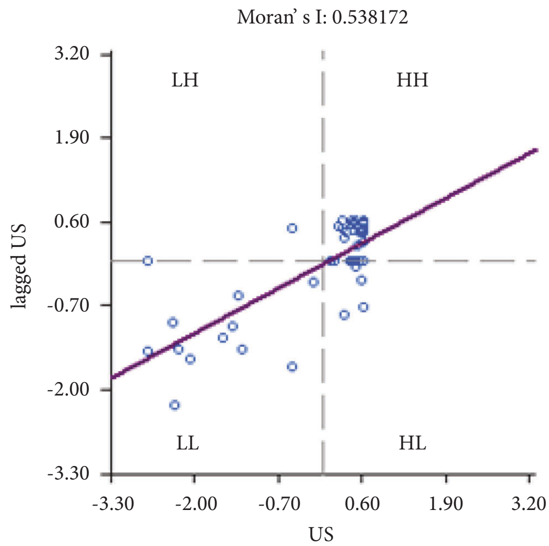

Figure 2: Moran's I index scatter diagram of urban shrinkage in China.

Table 2: Pearson correlation test.

Variable	$\ln PM_{2.5}$	lnUS	lnSE	lnGDP	lnPGA	lnLAND
$\ln PM_{2.5}$	1.0000					
lnUS	−0.4670***	1.0000				
	(0.0003)					
lnSE	0.3779***	−0.1510	1.0000			
	(0.0044)	(0.2710)				
lnGDP	0.3753***	−0.1257	0.3625***	1.0000		
	(0.0047)	(0.3602)	(0.0065)			
lnPGA	−0.3144**	0.1656	0.0042	−0.0625	1.0000	
	(0.0194)	(0.2267)	(0.9756)	(0.6502)		
lnLAND	−0.0072	0.6326***	0.0601	0.2058	−0.0258	1.0000
	(0.9580)	(0.0000)	(0.6625)	(0.1316)	(0.8513)	

Note. The value in () is the P value. $^{**}P < 0.05$. $^{***}P < 0.001$.

coefficients between variables were less than 0.63. Some of them, such as the one between lnUS and lnSE, failed the significance test.

Variance inflation factor (VIF) was employed to investigate the multicollinearity between variables. If VIF is greater than 5, there is multicollinearity. If it is greater than 10, there is severe multicollinearity. The VIF values of explanatory variables are shown in Table 3, all of which are less than 2.03, which indicates there was no multicollinearity between explanatory variables.

4.3.2. Spatial Diagnostic Test. As there have been many academic writings on the spatial agglomeration of urban haze pollution [30], we do not repeat it here. The above-given analyses show there was a significant spatial autocorrelation in China's urban shrinkage. A spatial econometric models selected through spatial diagnostic tests was used to check the impacts of urban shrinkage on haze pollution. As shown in Table 4, both LM-error and Robust LM-error passed the significance test at the 1% level, and neither LM-lag nor Robust LM-lag passed the significance test. Therefore, SEM was chosen [31].

4.3.3. Regression Results of Spatial Econometric Models. The regression results are shown in Table 5. The R^2 of SEM in the last column is 0.7137. In Table 4, the R^2 of the nonspatial measurement model is 0.4693. Therefore, it is more appropriate to use SEM to verify the impacts of urban shrinkage on haze pollution. The spatial autoregressive coefficients of all columns are positive and passed the significance test, which verified there was a spatial spillover effect in haze pollution, and that it is appropriate to use SEM for empirical analysis in this study.

The coefficient of urban shrinkage in each column is significantly negative, which means urban shrinkage had positive impacts on haze pollution, namely, it reduced haze pollution. This is because the decrease in urban population reduced residents' demand for cars and thus reduced car exhaust emissions. In the meanwhile, as cities shrank, green space increased due to land vacancy, which has boosted

Table 3: VIF test.

Variable	VIF	1/VIF
lnUS	2.0258	0.4936
lnSE	1.1860	0.8431
lnGDP	1.3007	0.7688
lnPGA	1.0673	0.9369
lnLAND	1.9840	0.5040

Table 4: Spatial diagnostic test.

Variable	coefficient	t-Statistic	P value
Constant	1.8924	2.3051	0.0254
lnUS	−1.5674	−3.8946	0.0003
lnSE	0.2371	1.9437	0.0576
lnGDP	0.1008	1.2374	0.2218
lnPGA	−0.2373	−1.8846	0.0654
lnLAND	0.1167	2.10016	0.0408
R^2	0.4693		
Spatial diagnostic test	MI/DF	Test value	P value
Moran's I	0.5209	4.6248	0.0000
LM-lag	1	0.6068	0.4359
Robust LM-lag	1	1.9676	0.1607
LM-error	1	17.8706	0.0000
Robust LM-error	1	19.2315	0.0000

Table 5: Estimation results of SEM.

Varable	(1)	(2)	(3)	(4)	(5)
λ	0.4335***	0.4651***	0.4930***	0.5924***	0.6169***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	3.7064***	2.5538***	0.9873	1.9588***	2.1173***
	(0.0000)	(0.0000)	(0.1616)	(0.0034)	(0.008)
lnUS	−1.0032***	−0.8888***	−0.7901**	−0.6270**	−1.005***
	(0.0043)	(0.0068)	(0.0120)	(0.0288)	(0.0012)
lnSE		0.3124***	0.2635***	0.2799***	0.2878***
		(0.0018)	(0.0058)	(0.0005)	(0.0001)
lnGDP			0.1742**	0.1663***	0.1027*
			(0.0103)	(0.0046)	(0.0892)
lnPGA				−0.3525***	−0.3398***
				(0.0001)	(0.0000)
lnLAND					0.0966**
					(0.0105)
R^2	0.4139	0.5082	0.5662	0.6741	0.7137
LR test	11.2965***	12.9077***	14.8669***	22.1554***	23.5316***
	(0.0000)	(0.0003)	(0.0001)	(0.0000)	(0.0000)

Note. The value in () is the P value. $^{*}P < 0.1$. $^{**}P < 0.05$. $^{***}P < 0.001$.

ecological restoration, improved air quality, and mitigated haze pollution. Regarding control variables, the proportion of secondary industries was significantly positive, which revealed the increase in the proportion of secondary industries aggravated haze pollution. The coefficient of economic development was significantly positive, which means economic development leads to haze pollution through expanding production scale and increasing the demand for energy consumption. The coefficient of green space in parks was significantly negative, which reveals that an expanded area of green space in parks reduced haze pollution. The coefficient of built-up areas was significantly positive, which indicates an expansion of built-up areas caused haze pollution due to smoke and dust emissions from real estate development, building construction, etc.

4.3.4. Analysis of Empirical Results by Region. To understand regional differences in the impacts of urban shrinkage on haze pollution, we conducted empirical tests on northeast, east, central, and west China. As there is a small quantity of samples in each region, it is not suitable to employ spatial quantitative analysis, so we adopted a common data model. To avoid possible endogeneity between variables, Phillips

Table 6: Unit root test in Northeast China (Unit root tests for the other three regions are available from the author).

	ADF	PP	ADF	PP
	Levels		First difference	
$lnPM_{2.5}$	0.4160 (0.7937)	0.6087 (0.8394)	−2.1427** (0.0350)	−4.8058*** (0.0001)
lnUS	−1.3689 (0.1533)	−1.4820 (0.1258)	−3.7123*** (0.0009)	−3.7123*** (0.0009)
lnSE	−0.24843 (0.5840)	−0.0575 (0.6514)	−4.5275 (0.0001)	−9.8039*** (0.0001)
lnGDP	0.2077 (0.7356)	−0.1881 (0.6058)	−7.8829*** (0.0000)	−13.7453*** (0.0001)
lnPGA	−0.8635 (0.3287)	−0.1957 (0.6031)	−9.4627*** (0.0000)	−9.4626*** (0.0000)
lnLAND	−0.2085 (0.5985)	−0.1168 (0.6310)	−5.4641*** (0.0000)	5.4640*** (0.0000)

Note. The value in () is the P value. $^{*}P < 0.1$. $^{**}P < 0.05$. $^{***}P < 0.001$.

Table 7: Estimation results of FMOLS regression in each region.

Variable	Northeast	East	Middle	West
Constant	3.8665***	4.9588**	2.5763***	3.7620***
	(0.0002)	(0.0382)	(0.0078)	(0.0082)
lnUS	−0.8147**	−0.5525*	−3.6561**	−0.3087
	(0.0186)	(0.0980)	(0.0250)	(0.9263)
lnSE	0.0132	1.5139**	0.1019*	0.5533**
	(0.8718)	(0.0290)	(0.0873)	(0.0208)
lnGDP	0.0626	−0.4959**	0.0147	−0.2666*
	(0.3148)	(0.0189)	(0.7743)	(0.0832)
lnPGA	−0.6109***	−0.5308*	0.0464	−0.3029*
	(0.0017)	(0.0690)	(0.5325)	(0.0903)
lnLAND	0.1349***	−0.1790**	0.1308**	0.3055**
	(0.0050)	(0.0364)	(0.0166)	(0.0134)
R^2	0.8167	0.7667	0.5207	0.5297

Note. The value in () is the P value. $^{*}P < 0.1$. $^{**}P < 0.05$. $^{***}P < 0.001$.

and Hansen [32] proposed FMOLS, a nonparametric method, to revise OLS estimators. On this basis, Pedroni [33] proposed FMOLS estimation for panel data which allows the estimation of heterogeneous cointegration vectors of panel members [34]. Pedroni's FMOLS method [35] is used in this study.

The stationarity of variables was tested before conducting regression. Unit root tests in northeast China alone are presented here to save space. As shown in Table 6, none level values of the variables passed ADF (Augmented Dickey-Fuller) and PP (Phillips-Perron) tests, but their first-order difference passed the two tests. Therefore, it is feasible to perform regression analysis herein.

The regression results of each region are shown in Table 7. Except for west China, the coefficients of lnUS were significantly negative. Urban shrinkage in central China had the greatest impacts on haze, followed by the northeast and the east. Urban shrinkage in the central, northeast, and east rose by 1 percentage point, which reduced haze pollution by 3.6561, 0.8147, and 0.5525 percentage points. This means shrinking cities in central, north and east China effectively alleviated haze pollution by reducing energy consumption and urban construction. Although the impact of urban shrinkage on haze pollution in west China was not significant, it was negative. That is, urban shrinkage in the west had positive impacts on mitigating haze pollution. The coefficients of lnSE in east, central, and west China were significantly positive. An increase in this proportion by 1 percentage point intensified haze pollution in east, central, and west China by 1.5139, 0.1019, and 0.5533 percentage points. The coefficients of lnGDP in east and west China were significantly negative, which indicates that economic development there alleviated haze pollution. The coefficients of lnPGA in northeast, east and west China were negative, that is, green area in parks in these regions reduced the degree of haze pollution. The coefficients of lnLAND in north, central, and west China were significantly positive, which means the increase in built-up areas in these regions aggravated haze pollution. However, the coefficient of lnLAND in east China was significantly negative. This is because, among the four regions, east China had the smallest built-up areas and actual construction areas, but shouldered the greatest population and resource pressure. Therefore, expanding built-up areas in east China and strengthening the construction of municipal structures and public facilities will help ease space pressure on urban traffic and reduce haze pollution.

5. Conclusions and Policy Implications

5.1. Conclusions. This study focuses on 55 shrinking cities selected by the urban shrinkage index using data about the urban population of 250 prefecture-level Chinese cities from 2012 to 2017. It analyzes the theoretical impacts of urban shrinkage on haze pollution and the spatial distribution and autocorrelation of urban shrinkage. The spatial error model (SEM) and the fully modified least squares (FMOLS) regression are used to empirically examine the impacts of urban shrinkage on haze pollution at national and regional levels. The results indicate that shrinking cities showed spatial agglomeration and that northeast China had the largest number of shrinking cities. Nationwide, urban shrinkage reduced haze pollution. An increase in the proportion of secondary industries, economic development, and built-up areas intensified haze pollution, while the increase in the green area in parks alleviated such pollution. Regionally, except for west China, the impacts of urban shrinkage on haze pollution were significantly negative. Urban shrinkage in central China had the greatest impacts on haze, followed by northeast China and east China. Haze pollution was intensified by the increase in the proportion of secondary industries in east, central and west China, alleviated by economic development in east and west China, slowed down by the increase in the green area in parks in northeast, east, and west China and aggravated by the rise in built-up areas in northeast, central, and west China [1].

5.2. Policy Implications. Based on the above-given conclusions, we proposed the following policy implications:

First, shrinking cities should adapt to urban shrinkage. According to urban development theory, cities go through birth, development, prosperity, and decline, so urban shrinkage is irreversible. Shrinking cities should take advantage of this trend to promote urban regeneration and stimulate vitality. The following measures are recommended: (1) demolish buildings like abandoned houses and workshops to build green spaces; increase the area of green spaces and wetlands to strengthen the adsorption of particulate matters, beautify the urban landscape and create more recreational spaces for residents. (2) Rationally plan urban area to improve the utilization of urban spaces; encourage the gathering of residential areas to improve the efficiency of public facilities; encourage remote companies to relocate to urban areas to reduce the use of private cars by employees. (3) Invest more in shrinking cities. With the outflow of essentials including population and firms, the tax revenues and fiscal capacities of shrinking cities are weakened, which is not conducive to public infrastructure construction and haze pollution management. Therefore, measures should be taken to improve the finance of shrinking cities by increasing subsidies and reducing or exempting taxes, so that shrinking cities have sufficient funds for constructing public facilities and controlling haze pollution.

Second, targeted measures should be adopted based on local conditions. Northeast China had the largest number of shrinking cities, so they should introduce preferential policies to retain talents and enterprises, promote the growth of local knowledge and technology, and build themselves into quality cities. Among the 55 sample cities, shrinking cities in the east had the highest proportion of secondary industries, which is a disadvantage for treating haze pollution. Therefore, they should vigorously develop high-tech industries and modern service industries, and expand built-up areas and green space in parks to reduce ecological pressure, thus reducing haze pollution. Shrinking cities in central China should speed up their economic development while lowering the ratio of secondary industries and raising that of tertiary industries. They had the largest built-up areas among the four regions and a positive coefficient of haze pollution. Therefore, they should reduce built-up areas and improve the efficiency of public facilities. In addition to increasing the proportion of tertiary industries, economic development, and green space in parks, they need to reduce built-up areas and optimize the allocation of stock assets.

Data Availability

Data will be made available on request: amylxhong@163.com.

Ethical Approval

This study was not funded by any organization. Author Xiaohong Liu declares that she has no conflict of interest. Xiaobo Wang declares that she has no conflict of interest. Tianrui Dong declares that he has no conflict of interest. This article does not contain any studies with human participants performed by any of the authors.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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