The Impact of Multi-Dimensional Urbanization on PM$_{2.5}$ Concentrations in 261 Cities of China

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ABSTRACT Rapid urbanization has caused serious PM$_{2.5}$ pollution. The existing researches mainly focus on the contribution of one aspect of urbanization to PM$_{2.5}$ concentrations. However, few studies have comprehensively considered the direct and indirect effects of multi-dimensional urbanization on PM$_{2.5}$ concentrations. In order to identify the impact of multi-dimensional urbanization on PM$_{2.5}$ concentrations, the entropy-right method, the spatial lag model, spatial error model and spatial Durbin model were used to investigate the relationships between multi-dimensional urbanization and PM$_{2.5}$ concentrations in 261 cities of China in 2016. Results demonstrated that the spillover effect of PM$_{2.5}$ concentrations between different cities was significant. Economic urbanization had the strongest direct effect on PM$_{2.5}$ concentrations. Social urbanization and ecological urbanization had a significantly negative impact on PM$_{2.5}$ concentrations in local cities. However, the biggest indirect effect on PM$_{2.5}$ concentrations in adjacent cities was social urbanization, followed by land urbanization. The direct and indirect effects of population urbanization on PM$_{2.5}$ concentrations were non-significant and the least. The findings from this result analysis and discussion can be used as a theoretical basis to provide some policy suggestions for China’s air governance and sustainable urban development.

INDEX TERMS PM$_{2.5}$ concentrations, multi-dimensional urbanization, spillover effects, spatial regression model.

I. INTRODUCTION

China has made extraordinary progress through a process of rapid urbanization on a massive scale in the past few decades. Urbanization is an important feature of China’s current development and has become the main driving force of domestic demand driven by the transformation of China’s economic structure. At the same time, some human activities related to urbanization have caused serious environmental pollution [1], especially haze pollution [2]. Frequent hazy weather across the country has seriously affected residents’ physical and mental health [3], traffic safety [4] and regional climate [5]. In particular, PM$_{2.5}$ (particulate matter with an aerodynamic equivalent diameter of 2.5 microns or less) is considered to be the “culprit” of haze weather [6]. PM$_{2.5}$ can not only reduce visibility, but also cause serious health damage to the nervous system, cardiovascular system, endocrine system, respiratory system and reproductive system of the human [7]–[10]. For now, although the Chinese government has taken some measures to reduce PM$_{2.5}$ concentrations [11], [12], PM$_{2.5}$ pollution is still a serious problem [13]. In the context of rapid urbanization and severe PM$_{2.5}$ pollution, improving urban air quality in China has become the top priority of air pollution prevention and control. Hence, studying the relationship between PM$_{2.5}$ concentrations and urbanization will help us to have a clear understanding of PM$_{2.5}$ pollution. It also provides a new perspective on sustainable urban development and takes more effective measures to improve air quality.

Since the reform and opening-up, China’s urbanization has undergone a unique and complex transformation process of socioeconomic factors. Moreover, all these socioeconomic...
between urbanization and PM concentrations. Different scholars explored the relationship between urbanization and PM concentrations. PM concentrations would inevitably be affected by urbanization. Urbanization has multi-dimensional properties, such as population growth, economic development, urban land expansion, social lifestyle change. Nevertheless, not every dimension of urbanization has a positive impact on PM concentrations. Different scholars explored the relationship between urbanization and PM concentrations from different dimensions and came up with different viewpoints. Firstly, population urbanization was often measured by a single index, namely the percentage of the urban population in the total population. Prior studies pointed out that PM concentrations increased with the growth of population urbanization in China and the Yangtze River Economic Belt. However, the relationship between population urbanization and PM concentrations varies with regions. The relationship between PM concentrations and population urbanization presented an inverted U-shaped Environmental Kuznets Curve (EKC) in the whole China and its central and western region, but showed a N-shaped EKC in the developed eastern region of China. Secondly, economic urbanization was usually reflected by GDP density, GDP and GDP per capita. Some scholars verified that the relationship between PM pollution and economic urbanization fitted the EKC hypothesis. For example, there was an inverted U-shaped or N-shaped relationship between economic urbanization and PM concentrations in China. Economic urbanization contributed a lot to PM concentrations in China’s Yangtze River Economic Belt. Economic growth, fossil energy consumption, fuel consumption, and coal combustion were positively correlated with PM concentrations. On the contrary, increased energy intensity and adjustment of the industrial structure were conducive to reducing PM emissions. Thirdly, land urbanization reflects urban land expansion. The urban built-up area contributed to the increase of PM concentrations. Dense buildings were not conducive to the dispersion of PM concentrations. Conversely, public transportation infrastructure investment and Well-ventilated design of roads and buildings can promote the reduction of PM emissions. Fourthly, in terms of social urbanization, private cars’ secondary pollutants and primary emissions were one of the main sources of PM pollution. Production and transportation related to international trade (or interprovincial trade) had played a positive role in PM pollution.

Based on the existing research results, it can be known that the impact of urbanization on PM concentrations is multi-dimensional. However, the existing empirical studies mainly focus on the relationship between uni-dimensional urbanization and PM concentrations. At the city scale, few studies have comprehensively considered the contribution of multi-dimensional urbanization to PM concentrations in China, such as population, economy, land, society and ecological environment. Besides, precipitation, relative humidity, temperature, wind speed, air pressure, and radiation and other meteorological factors also had a significant impact on PM concentrations in most studies. To better explore the relationship between urbanization and PM concentrations from different perspectives, it is necessary to use meteorological factors to control the relationship analysis and improve the reliability of the model. In this study, PM station data, five meteorological factors and urbanization factors of five dimensions in 261 cities of China were selected (Figure 1). It is noted that we have incorporated ecological urbanization into one aspect of multi-dimensional urbanization. According to the National New-type Urbanization Plan, the new-type urbanization is a more human-centered and environmentally-friendly urbanization process. Therefore, ecological urbanization is also very important.

And the impact of multi-dimensional urbanization on PM concentrations was investigated comprehensively. Furthermore, the direct and spillover effects of urbanization on PM concentrations were explored from different dimensions. The findings from this study can provide some auxiliary policy suggestions for China’s air governance and sustainable urban development.

II. DATA AND METHODS

A. PM CONCENTRATIONS

In order to show the PM pollution status of the various cities comprehensively and objectively, the dataset on the hourly PM concentrations from China’s environmental monitoring stations in various cities was collected as raw data. For each city, the daily PM concentrations were the average value of the hourly PM concentrations of all available local monitoring stations. According to the daily average PM concentrations, the annual average PM concentrations in Chinese cities in 2016 were calculated by the arithmetic average method.

B. METEOROLOGICAL FACTORS

The meteorological data were from the China Meteorological Administration. Monthly meteorological data of 706 meteorological observation stations in 2016 were collected. Precipitation (PRC), air pressure (PRS), wind speed (WS), temperature (TEM) and relative humidity (RH) were selected. First, missing and error data from the initial dataset were eliminated by data cleaning. Secondly, the annual average of air pressure, wind speed, temperature, and relative humidity were obtained by the arithmetic average method. The annual precipitation of each meteorological station was the sum of 12 months’ precipitation. Thirdly, the annual average meteorological data for each city was obtained by taking the average meteorological data of all stations in the city.
C. COMPREHENSIVE URBANIZATION FACTORS

Comprehensive urbanization factors mainly came from the China Statistical Yearbook 2017 (http://www.stats.gov.cn/). The proportion of the urban population and per capita disposable income of urban households were obtained from provincial statistical yearbooks, city-level statistical yearbooks and Statistical Communiqué of the National Economic and Social Development in 2016. Urban population density, area of built district, area of urban construction land, public recreational green space per capita and green coverage rate of built district were from China Urban-Rural Construction Statistical Yearbook 2017 (http://tongji.cnki.net/kns55/index.aspx). GDP, the secondary industry as percentage to GDP, the tertiary industry as percentage to GDP, total retail sales of consumer goods were collected through China City Statistical Yearbook 2017 (http://tongji.cnki.net/kns55/index.aspx).

Before data analysis, all data described above were standardized by min-max normalization. These data were converted into dimensionless pure values to facilitate the comparison and weighting of indicators of different units. PM$_{2.5}$ concentrations dataset, meteorological factors dataset and comprehensive urbanization factors dataset were matched by cities. And the cities with incomplete data were eliminated. Finally, data sets of 261 cities were left. Hence, as shown in Figure 1, the remaining 261 cities were selected as our research area in the paper.

D. MEASURE OF COMPREHENSIVE URBANIZATION

The comprehensive urbanization (CU) in this study includes five subsystems, namely, population urbanization (PU), economic urbanization (EU), land urbanization (LU), social urbanization (SU) and ecological urbanization (ECU). The entropy-right method was used to calculate the weight of comprehensive urbanization factors. According to the weight of each index, comprehensive urbanization was calculated. The specific calculation process was as follows:

The proportion of the indicator $j$ in city $i$:

\[ P_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}} \]  

(1)

Determine the entropy of indicator $j$:

\[ e_j = -\frac{\sum_{i=1}^{m} (P_{ij} \times \ln P_{ij})}{\ln m} \]  

(2)

Calculate the entropy weight of indicator $j$:

\[ w_j = \frac{(1 - e_j)}{\sum_{j=1}^{n} (1 - e_j)} \]  

(3)
Comprehensive urbanization in city $i$:

$$U_i = \sum_{j=1}^{n} w_j \cdot r_{ij}$$

where $r_{ij}$ denotes standard values of the indicator $j$ in city $i$. $m$ is the number of cities. $n$ represents the number of index. According to the above formula (1)-(3), the weight of each index of comprehensive urbanization was calculated, and the results were shown in Table 1. The spatial distribution of the comprehensive urbanization of 261 cities was shown in Figure 2b. Similarly, we also used the entropy-right method to calculate the respective index weights of urbanization subsystems and the urbanization of each dimension. The spatial distributions of PU, EU, LU, SU and ECU were shown in Figure 2c-g.

E. SPATIAL REGRESSION MODELS

Spatial data have spatial autocorrelation and spatial heterogeneity. In statistical analysis, ignoring spatial dependence between spatial data would lead to deviation of analysis...
TABLE 1. Evaluation weight of urbanization.

| Subsystem of Urbanization | Index                     | Weight |
|---------------------------|---------------------------|--------|
| Population                | The proportion of urban population | 0.092  |
|                           | Urban population density   | 0.132  |
| Economic                  | Gross domestic product     | 0.084  |
|                           | Secondary industry as percentage to GDP | 0.084  |
|                           | Tertiary industry as percentage to GDP | 0.095  |
| Land                      | Area of built district     | 0.102  |
|                           | Area of urban construction land | 0.065  |
| Social                    | Total retail sales of consumer goods | 0.093  |
|                           | Per capita disposable income of urban households | 0.143  |
| Ecological                | Public recreational green space per capita | 0.064  |
|                           | Green coverage rate of built district | 0.046  |

results. However, the traditional statistical theory requires that sample data are independent of each other. Different from traditional regression models, spatial regression models can make good use of the spatial characteristics to analyze the data. Therefore, spatial regression models are more suitable for PM$_{2.5}$ pollution analysis. PM$_{2.5}$ pollution may occur in the following three ways, (1) the spillover effect of PM$_{2.5}$ pollution may exist between adjacent cities. (2) PM$_{2.5}$ concentrations are not only affected by urbanization and natural factors in the local city, but also may be affected by these factors in surrounding cities. (3) The disturbance between the error terms may also affect PM$_{2.5}$ concentrations. In this study, the spatial lag model (SLM), spatial error model (SEM) and spatial Durbin model (SDM) were used to verify the three possible ways to influence PM$_{2.5}$ concentrations. The SLM, SEM, and SDM can be expressed by:

$$Y = \alpha \tau_n + \rho WY + X\beta + \epsilon, \epsilon \sim N(0, \delta^2 I_n)$$ (5)

$$Y = \alpha \tau_n + X\beta + \lambda W\mu + \epsilon, \epsilon \sim N(0, \delta^2 I_n)$$ (6)

$$Y = \alpha \tau_n + \rho WY + X\beta + WX\theta + \epsilon, \epsilon \sim N(0, \delta^2 I_n)$$ (7)

where $N$ is the number of cities. $Y \in \mathbb{R}^{N \times 1}$ is an vector of PM$_{2.5}$ concentrations. $X \in \mathbb{R}^{N \times M}$ is a matrix of explanatory variables. $\mu \in \mathbb{R}^{N \times 1}$ is a vector of residuals. $W\mu \in \mathbb{R}^{N \times 1}$ denotes the interaction effects among the error term of different cities. $\beta$ is the coefficient of explanatory variables. $\theta$ is the coefficient of $WX$. $I_n$ is an $n$-dimensional identity matrix. $\epsilon$ is a vector of normally distributed errors.

The direct effect is the effect of a change of a particular explanatory variable in a particular city on the dependent variable of the same city. The indirect effect can also be called spillover effect, which means the effect of a change of a particular explanatory variable in a particular city on the dependent variable of the other cities. Both SLM and SDM include direct effect and spillover effect. But in SLM, the ratio between the spillover and direct effects is the same for every explanatory variable, which is unlikely to be the case in many empirical studies [40], [41]. Therefore, SDM was chosen to estimate the direct effect and spillover effect of explanatory variables. In SDM, the partial derivative method was used to divide the direct effect and indirect effect of explanatory variables on PM$_{2.5}$ concentrations [40]–[42]. In the article [41], for the $k$ th explanatory variable, the diagonal elements of the matrix $(I - \rho W)^{-1}[\beta_k + W\theta_k]$ represent the direct effect, while the indirect effect is reflected by the off-diagonal elements of the matrix $(I - \rho W)^{-1}[\beta_k + W\theta_k]$.

In the three spatial regression models, the endogenous interaction effects among PM$_{2.5}$ concentrations can be estimated by the SLM [43], [44]. The interaction effects among the error terms can be reflected by the SEM [43], [44]. The SDM can not only reflect the endogenous interaction effects among dependent variables, but also reflect the exogenous interaction effects among independent variables [40], [42], [45]. In the study, the three spatial regression models were all based on the ordinary least squares (OLS). The Lagrange multiplier (LM) test and robust Lagrange multiplier (RLM) test were used to judge whether SLM or SEM was more suitable. According to the values of the log-likelihood function in the different spatial regression models, different models were compared by the goodness of fit test and likelihood ratio test (LR). The maximum likelihood method (ML) was used for parameter estimation. ArcGIS10.3 was used to produce inverse distance spatial weight and draw graphs. All the regression analysis was implemented using the spatial regression toolbox in MATLAB R2015b.

III. RESULTS

A. THE SPATIAL DISTRIBUTION OF PM$_{2.5}$ CONCENTRATIONS AND URBANIZATION

Spatial distributions of PM$_{2.5}$ concentrations and urbanization in 261 cities of China in 2016 were shown in Figure 2. From Figure 2a, the annual average PM$_{2.5}$ concentrations in 261 cities all exceeded 10 $\mu g/m^3$. According to the World Health Organization (WHO) health standards, PM$_{2.5}$ concentrations above 10$\mu g/m^3$ begin to affect human health [46]. However, PM$_{2.5}$ concentrations in most cities were above 35$\mu g/m^3$. And some cities have concentrations of more than 70$\mu g/m^3$. It’s worth noting that most of the cities with high PM$_{2.5}$ pollution were located in economically developed cities, such as the Beijing-Tianjin-Hebei region, the Pearl
River Delta Region and Eastern China (Figure 2d). From Figure 2b,d, the top four cities for CU and EU were Beijing, Shanghai, Guangzhou and Shenzhen. Half of 261 cities had PU of more than 30% (Figure 2c). From Figure 2e, the LU of Beijing, Chongqing, Shanghai, Guangzhou, Tianjin and Dongguan all exceed 60%. From Figure 2f, the SU of Shanghai, Beijing, Guangzhou, Suzhou, Hangzhou, Nanjing, Shenzhen was also more than 60%. More than 90 percent of cities were ecologically urbanized above 30 percent in Figure 2g.

TABLE 2. OLS, SLM, SEM and SDM estimation in 261 cities based on the impact of comprehensive urbanization on PM$_{2.5}$.

| Variable | OLS  | SLM  | SEM  | SDM  |
|----------|------|------|------|------|
| CU       | 0.058| 0.067*| 0.075*| 0.078**|
| PRC      | -0.253***| -0.254***| -0.265***| -0.301***|
| PRS      | 0.303***| 0.211***| 0.183***| 0.106*|
| WS       | -0.141***| -0.131***| -0.131***| -0.139***|
| TEM      | 0.165***| 0.162***| 0.153***| 0.208***|
| RH       | -0.168***| -0.105***| -0.103***| -0.053|
| W$^{+}$CU| -0.062| -0.297| 0.485***| 0.061***|
| W$^{+}$PRC| -0.297| -0.297| 0.485***| 0.061***|
| W$^{+}$PRS| -0.297| -0.297| 0.485***| 0.061***|
| W$^{+}$PM2.5 | 0.584***| 0.584***| 0.584***| 0.584***|
| W$^{+}$µ | 0.337| 0.400| 0.426| 0.457|
| R$^{2}$   | 0.321| 0.386| 0.413| 0.430|
| Adjust R$^{2}$ | 0.321| 0.386| 0.413| 0.430|
| SLM-LM   | 66.976***| 66.976***| 66.976***| 66.976***|
| SLM-RLM  | 42.515***| 42.515***| 42.515***| 42.515***|
| SEM-LM   | 33.710***| 33.710***| 33.710***| 33.710***|
| SEM-RLM  | 9.249***| 9.249***| 9.249***| 9.249***|
| Log-L    | 231.412| 341.743| 335.400| 350.009|
| LR-SLM   | 16.669***| 16.669***| 16.669***| 16.669***|
| LR-SEM   | 29.196***| 29.196***| 29.196***| 29.196***|

Notes: *, **, *** represent coefficients are significant at the 10%, 5%, 1% levels, respectively.

B. THE IMPACT OF COMPREHENSIVE URBANIZATION ON PM$_{2.5}$ CONCENTRATIONS

The Ordinary Least Squares (OLS) was first used as a benchmark model. The Lagrangian multiplier (LM) and robust LM (RLM) test were used to determine whether OLS needs to be developed into a spatial regression model. As shown column 2 of Table 2, SLM-LM, SEM-LM, SLM-RLM and SEM-RLM were significant (p<0.01). This means that the null hypothesis that there was no spatial lag or spatial error was rejected. Below, three spatial regression models (SLM, SEM or SDM) were introduced to estimate the impact of comprehensive urbanization on PM$_{2.5}$ concentrations.

However, which spatial regression model was the best? The likelihood ratio (LR) was selected as the parameter for comparison of multiple models. According to the estimates of SDM in column 5 of Table 2, LR-SLM, and LR-SEM were significant, and p values were less than 0.05. This proved that SDM can neither be simplified to SLM nor SEM. Moreover, log-likelihood value (Log-L) and R$^{2}$ of SDM were 350.009 and 0.457 respectively, which were the highest among all models. These indicated that SDM was superior to SLM and SEM. More importantly, the interaction effects of endogenous and exogenous were taken into account in SDM, which can better describe the impact of urbanization on PM$_{2.5}$ concentrations. Hence, the direct effect and spillover effect of urbanization on PM$_{2.5}$ concentrations were identified by SDM (Table 4). In other words, SDM can better explain the fact that PM$_{2.5}$ concentrations were affected not only by local urbanization but also by the urbanization of surrounding cities. The spatial models showed robustness when different spatial weighting matrixes (inverse distance weight or queen contiguity weight) were employed. Because the spatial models based on inverse distance weighting matrix fitted better than the spatial models based on the queen contiguity weighting matrix. Therefore, the inverse distance weighting matrix was chosen in our research.

As shown in Table 2, at the 99 percent confidence interval, W$^{+}$PM$_{2.5}$ of SLM and SDM were significant. This result reflected PM$_{2.5}$ pollution existed a significant spillover effect, and PM$_{2.5}$ pollution in surrounding areas did affect local PM$_{2.5}$ concentrations. Excluding the influence of other factors on PM$_{2.5}$ concentrations, every 1% increase in the average PM$_{2.5}$ concentrations of surrounding cities caused the average PM$_{2.5}$ concentrations in the local city to increase by more than 3%. Besides, in the SLM, SEM, and SDM, there was a significant and positive impact of comprehensive urbanization on PM$_{2.5}$ concentrations. The influence of PRS and TEM in local cities on PM$_{2.5}$ concentrations were all positive and significant in the three spatial regression models.

But PRC and WS in local cities presented a significantly negative effect. In addition to SDM, RH in local cities also presented a significantly negative effect. In local cities, PM$_{2.5}$ concentrations decreased with PU increased in local cities. Notably, the coefficient of PU was negative and insignificant. This implied that there was a negative and insignificant correlation between PU and PM$_{2.5}$ concentrations, and PM$_{2.5}$ concentrations in local cities contributed the most to PM$_{2.5}$ concentrations. Although a significant and positive correlation between PM$_{2.5}$ concentrations and CU were concluded in Section III, B, not every dimension of urbanization had the same effect on PM$_{2.5}$ concentrations. How does multi-dimensional urbanization affect PM$_{2.5}$ concentrations? To answer this question, urbanization of different dimensions was incorporated into SDM as explanatory variables in the study. The experimental results were shown in Table 3. The coefficient of EU was the largest, positive and significant, indicating that economic urbanization in local cities contributed the most to PM$_{2.5}$ concentrations. The effect of LU in local cities on PM$_{2.5}$ concentrations was also positive but not significant. While the coefficient of PU was negative and insignificant. This implied that there was a negative and insignificant correlation between PU and PM$_{2.5}$ concentrations, and PM$_{2.5}$ concentrations decreased with PU increased in local cities. Notably, SU and ECU had a significantly negative impact on PM$_{2.5}$ pollution. Except for RH, PM$_{2.5}$ concentrations were significantly affected by other meteorological factors in the local area.
cities. Furthermore, PRS and TEM had a significant positive effect on PM$_{2.5}$ concentrations while PRC and WS had a significant negative effect on PM$_{2.5}$ concentrations in local cities.

The estimation results about the direct and indirect effects in SDM were shown in Table 4, urbanization of different dimension had different direct and indirect effects on PM$_{2.5}$ concentrations. Ignoring the positive and negative signs of the values and taking the numerical size and significance as the ranking criteria, the direct impact of multi-dimensional urbanization on PM$_{2.5}$ concentrations was classified as follows: economic urbanization (EU) > social urbanization (SU) > ecological urbanization (ECU) > land urbanization (LU) > population urbanization (PU). However, the order of the indirect effects of LU was social urbanization (SU) > land urbanization (LU) > ecological urbanization (ECU) > economic urbanization (EU) > population urbanization (PU). The biggest indirect influence on PM$_{2.5}$ concentrations was social urbanization (SU). From row 1 and row 3 of Table 4, it can be found that the direct, indirect and total effects of CU and EU on PM$_{2.5}$ concentrations had consistent results. These suggested that the EU contributed more to PM$_{2.5}$ concentrations than urbanization of other dimensions [24].

From Table 4, the coefficients of direct effects of CU and EU were 0.078 ($p<0.05$) and 0.322 ($p<0.01$), respectively, indicating that excluding the influence of other factors on PM$_{2.5}$ concentrations (e.g., the residuals, etc.), for every 1% increase in CU and EU, PM$_{2.5}$ concentrations in one city increased by 0.078% and 0.322%, respectively. On the contrary, at a significant level of 5%, the direct effects of SU and ECU were $-0.198$ and $-0.108$, respectively. This indicated that excluding the influence of other factors on PM$_{2.5}$ concentrations(e.g., the residuals, etc.), for every 1% increase in a city’s SU and ECU, PM$_{2.5}$ concentrations would decrease by $-0.198%$ and $-0.108%$, respectively. Moreover, the differences between the coefficients of point estimates in SDM (Table 2 and Table 3) and the coefficients of direct effects (Table 4) result from feedback effects. The direct effect estimates include feedback effects that arise as a result of impacts passing through neighboring cities and back to the city where the change instigated. For example, the coefficient of EU in SDM in Table 3 is 0.332 while the direct effect in Table 4 is 0.322, resulting in a feedback effect of $-0.01$. The coefficient of indirect effects of SU was 0.579 and significant ($p<0.05$), indicating that SU had a positive impact on PM$_{2.5}$ concentrations in nearby cities. The coefficient of indirect effects of LU was $-0.481$ at the significant level of 10%. It meant that LU had a negative influence on PM$_{2.5}$ concentrations in adjacent cities. It’s worth noting that the coefficients of W*$X$ in Table 2 and Table 3 and indirect effect in Table 4 have different meanings. The coefficients of W*$X$ represent how explanatory variables of neighboring regions affect PM$_{2.5}$ pollution in this region, while the coefficients of indirect effect reflect how explanatory variables of this city affect PM$_{2.5}$ pollution in adjacent regions.

IV. DISCUSSION

A. EXPLANATION FOR DIRECT AND INDIRECT EFFECTS OF MULTI-DIMENSIONAL URBANIZATION ON PM$_{2.5}$ CONCENTRATIONS

From row 2 of Table 4, the direct effect of population urbanization (PU) on PM$_{2.5}$ concentrations was negative and insignificant. This may be related to the dual effects of population urbanization (PU) on PM$_{2.5}$ concentrations. Some scholars also pointed out that population urbanization (PU) and PM$_{2.5}$ concentrations presented an inverted U-shaped relationship in China [23]. Population urbanization (PU) was a dynamic process of the non-urban population constantly transforming into cities. In terms of positive effect, urban population growth would lead to more living, housing and transportation demand, such as coal burning [47], motor vehicle exhaust emission [48] and electricity consumption [49]. All of these contributed to the increase of PM$_{2.5}$ concentrations. Moreover, with the continuous increase of the urban population, there would inevitably be more urban household waste. At present, incineration had become one of the main methods of urban waste disposal. The waste incineration also increased PM$_{2.5}$ concentrations [50]. From the perspective of
negative effect, the urban population was more concentrated than the rural population, which would improve public energy efficiency and cleaner fuel types [51]. The more concentrated the population, the more efficient the shared infrastructure would be [52]. For example, taking public transportation (shared bikes, Shared cars, bus, subway and so on) can alleviate PM$_{2.5}$ pollution [53]. In addition, many cities had implemented urban population control policies. The reduction of urban population can also reduce energy and resource consumption, thus reducing PM$_{2.5}$ concentrations [54]. Dual effects could be offset among cities, making the average impact of population urbanization on PM$_{2.5}$ concentrations insignificant in the whole China. The direct, indirect, and total effect of PU on PM$_{2.5}$ concentrations were all non-significant, indicating the PU had a small impact on PM$_{2.5}$ concentrations.

Economic urbanization refers to the process of human society’s continuous transformation from traditional agricultural society to industrialized society. From row 3 of Table 4, economic urbanization (EU) had no significant spillover effect on PM$_{2.5}$ pollution in neighboring cities, but its direct effect on PM$_{2.5}$ pollution in the local city was significant and positive. It is largely attributed to increased emissions from various energy consumption factories. In the course of economic development, the labor force is constantly shifting from primary industry to secondary and tertiary industry. This will lead to the expansion of the industrial scale and the increase in energy consumption. And most factories in China burn coal. Coal burning was positively correlated with PM$_{2.5}$ concentrations [47]. Some scholars had discovered that the proportion of the secondary industry and the total emissions of industrial sulfur also contributed to the PM$_{2.5}$ concentrations [55]. Although the progress of production technology, the adjustment of industrial structure and the improvement of energy intensity can reduce PM$_{2.5}$ pollution [32], [56]; the production technology of many cities is relatively backward, the industrial structure is dominated by heavy industry, and the energy efficiency is not high, all of which need to be improved.

The urbanization process of land is mainly manifested as the increase of built-up area. From row 4 of Table 4, LU had a positive and non-significant impact on PM$_{2.5}$ concentrations in the local city; however, the spillover effect is significant and negative. This may be attributed to the station density of public transportation and ventilation design of roads and buildings. Station density of public transportation was negatively correlated with PM$_{2.5}$ concentrations, and improving the accessibility of public transportation can reduce the use of private cars [33]. Well-ventilated roads and buildings contributed to the dilution and diffusion of PM$_{2.5}$ concentrations [34]. In the long run, investment in urban transport infrastructure can reduce pollution emissions by reducing congestion through proper road network planning [35]. Thus, the convenient and well-ventilated infrastructure design in a city is beneficial to reduce the spillover effect on PM$_{2.5}$ pollution in neighboring cities.

Social urbanization (SU) reflects the changes of residents’ social lifestyle. SU was reflected by two indicators, namely total retail sales of consumer goods and per capita disposable income of urban households in the paper. From row 5 of Table 4, the direct effect of SU on PM$_{2.5}$ concentrations was negative and significant. That’s probably because when people move from the countryside to the city, changes in lifestyle would increase the demand for energy, which would increase PM$_{2.5}$ emissions. But the energy-saving effect of urbanization increased when income levels increased, reducing PM$_{2.5}$ emissions [57]. Although the contribution of total retail sales to PM$_{2.5}$ pollution was very high [38] and trade of intermediate products also contributed to an increase in PM$_{2.5}$ related emissions, trade of final products generated savings in PM$_{2.5}$ related emissions [58]. However, SU had a significant positive indirect effect on PM$_{2.5}$ pollution in adjacent cities. Because of production and transportation related to international trade (or interprovincial trade) can indirectly produce PM$_{2.5}$ pollution [37], [38]. Here the indirect effect and direct effect of SU were all significant, but the total effect of SU was consistent with the indirect effect. It indicated that the spillover effect of SU was stronger than the direct effect. This may be caused by the frequent trade between urban agglomerations. Trade cooperation between urban agglomerations not only brings certain economic benefits, but also brings certain pollution, such as vehicle exhaust emissions.

Ecological urbanization (ECU) is mainly manifested by the two factors, namely public recreational green space per capita and green coverage rate of built district in the study. From row 6 of Table 4, the direct effect of ECU on PM$_{2.5}$ concentrations was negative and significant. Some scholars also pointed out that the effectiveness of PM$_{2.5}$ emission reduction depended on the green space coverage rate [59]. For example, PM$_{2.5}$ concentrations near schools were low because of the high number of green plants around schools [60]. Moreover, the greening of urban areas also increased year by year. According to China Urban-Rural Construction Statistical Yearbook, in 2002, Beijing, Tianjin, and Shanghai had a green coverage rate of built district of 40.49%, 27.30% and 29.40%, respectively. They had increased to 48.4%, 37.22%, and 38.6% respectively in 2016. The three effects of ECU on PM$_{2.5}$ concentrations were all negative, especially the direct effect was significantly negative. It suggests that greening plays an irreplaceable role in PM$_{2.5}$ pollution control of the local city. Meanwhile, the greening of surrounding cities is also of great importance to the city, meaning that the sustainable development of urban agglomeration is also very important to improve the atmospheric environment.

B. IMPLICATION FOR SUSTAINABLE URBAN DEVELOPMENT

Environmental pollution caused by urbanization has aroused the government’s great attention, especially PM$_{2.5}$ pollution. Understanding the relationship between urbanization and PM$_{2.5}$ pollution will contribute to sustainable urban development and improve public health. According to the research
results, four implications for sustainable urban development were proposed as follows:

(1) Economic urbanization was the most important factor contributing to the rise of PM$_{2.5}$ concentrations. In the future industrial development as far as possible to use some clean energy to reduce coal consumption, such as water energy, wind energy, solar energy, and tidal energy. At the same time, energy efficiency and production technology should be improved.

(2) Because dense buildings are not conducive to dissipating pollutants. Buildings and urban roads can be designed with more consideration for ventilation.

(3) Improving the efficiency of public transportation can reduce people’s use of private cars, which helps to reduce PM$_{2.5}$ emissions. The convenience of transfer between public transport and the accessibility of public transport should be considered in urban planning. All this has the potential to make public transport more efficient.

(4) Ecological urbanization can reduce PM$_{2.5}$ concentrations. The greening of the city needs to be strengthened. Furthermore, the ecological garden is an important foundation for sustainable urban development.

V. CONCLUSIONS

In the study, 261 cities in China were selected as a study area. Based on the spatial lag model, spatial error model and spatial Durbin model, the direct and indirect effects of multi-dimensional urbanization on PM$_{2.5}$ concentrations for 261 cities across China in 2016 were investigated. The results demonstrated that there is a significant spatial spillover effect of PM$_{2.5}$ concentrations between different cities. For direct effect, economic urbanization was the most significant factor to affect local PM$_{2.5}$ concentrations, followed by social urbanization, ecological urbanization, land urbanization, and population urbanization. Social urbanization and ecological urbanization in local cities had a significantly negative correlation with PM$_{2.5}$ concentrations. However, from the perspective of indirect effect, social urbanization had the strongest spillover effect on PM$_{2.5}$ concentrations. Only the spillover effect of land urbanization and social urbanization on PM$_{2.5}$ concentrations was significant. The effect of population urbanization on PM$_{2.5}$ concentrations was the weakest and non-significant in both local and surrounding cities. The direct, indirect and total effects of comprehensive urbanization and economic urbanization on PM$_{2.5}$ concentrations had consistent results. The PM$_{2.5}$ pollution caused by economic urbanization can be alleviated by adjusting the industrial structure, improving technology and using clean energy. Ventilation of urban buildings and roads, accessibility of public transport stations and greening in urban planning all contribute to the reduction of PM$_{2.5}$ concentrations.

These results and discussion can provide decision support for China’s air governance and sustainable urban development, so as to take more effective measures to improve air quality.

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