Temporal and Spatial Distribution Characteristics of Air Pollution and the influence of Energy Structure in Guangdong-Hong Kong-Macao Greater Bay Area

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Abstract. Based on the panel data of 11 cities in GBA from 2010 to 2016, this paper uses spatial data analysis method to study the temporal and spatial distribution characteristics of air pollution, and the impact of energy structure on air pollution in GBA. The results show that the more serious air pollution is mainly distributed in Zhaoqing, Foshan, Jiangmen, etc. Air pollution has spatial correlation and obvious “path dependence” characteristics in spatial distribution. Secondly, the energy structure coefficient is positive, which means that the coal consumption increases 1%, the air pollution index will rise by 0.1381%. At the same time, a “U”-type relationship exists between per capita GDP and air pollution.

1. Introduction
The Opinions about More Effective Regional Coordination and Development Mechanism issued by the Central Committee of the Communist Party of China and the State Council clearly point out that Hong Kong, Macao, Guangzhou and Shenzhen are the center cities to lead the construction of Guangdong-Hong Kong-Macao Greater Bay Area (GBA), and promote the green development of Pearl River Delta region. However, with the development of economy and society, the problem of air pollution begin to become more prominent. Especially, PM$_{10}$ pollution as the main representative has become more and more serious. To rectify air pollution problem, we must consider the spatial effects and the impact of energy structure on air pollution. Therefore, this paper studies the temporal and spatial distribution characteristics of air pollution and the impact of energy structure on air pollution in GBA.

The issue of energy consumption to air pollution has always been one of the research focuses, and the existing literature revealed the relationship between energy consumption and air pollution. Auffhammer and Carson (2008) [1] use regional exhaust emissions as a variable for carbon dioxide emissions, and verify the existence of the CO$_2$ Environment Kuznets Curve (EKC). Subsequently, based on six Central American countries, Apergis and Payne (2009) [2] find a one-way causal relationship from energy consumption to environmental pollution in the short term. Acaravci and Ozturk (2010) [3] also constructs a distribution lag model for energy consumption, carbon dioxide and economic growth, confirming the existence of EKC in Germany and Italy. Katircioglu (2014) [4] analyzes the impact of international tourism and energy consumption on local environmental pollution in Turkey. The study finds that there is a long-term equilibrium relationship between tourism, energy consumption and carbon dioxide emissions. Bastola and Sapkota (2015) [5] also use a time series model to analyze the causal relationship between energy consumption and environmental pollution in Nepal, and shows that there is a long-term two-way causal relationship between energy consumption and carbon emissions, and energy
consumption will lead to an increase in carbon emissions. In addition, the literature mainly uses CO$_2$ and SO$_2$ to measure air pollution, with less PM$_{10}$ discussed as air pollution indicators. Research on the spatial impact of energy structure on air pollution in GBA is worth discussing.

2. Methods

2.1. Study area

Figure 1 shows the Guangdong-Hong Kong-Macao Greater Bay Area, including Guangzhou (GZ), Zhaoqing (ZQ), Foshan (FS), Dongguan (DG), Huizhou (HZ), Jiangmen (JM), Zhongshan (ZS), Shenzhen (SZ), Zhuhai (ZH), Hong Kong (HK), Macao (MC). As one of China’s current national key economic development, the GBA is an area of 55,904 km$^2$ in South China, and it created 13% of the national Gross Domestic Product (GDP) in 2016. Meanwhile, the GBA is a highly urbanized city cluster, with an average inter-city distance shorter than 10 km, which makes the prevention and control of transboundary air pollution a severe challenge [6].

![Figure 1. The Guangdong Province, Hong Kong and Macao region.](image)

2.2. Variables and data

As the panel data has larger sample size, which can control the heteroscedasticity between different regions and the bias caused by neglected variables, this study selects 11 cities’ panel data from 2010 to 2016 in GBA as the research subject. In this paper, air pollution is measured by the annual average concentration values of PM$_{10}$, energy structure indicator is measured by the proportion of coal to total energy consumption. Meanwhile, based on the EKC, this paper selects the actual per capita GDP and its squared as explanatory variables, which illustrates the economic development level. The related data is derived from the Statistical Statistical Yearbooks and Guangdong-Hong Kong-Macao Pearl River Delta Regional Air Quality Monitoring Network. Table 1 lists the descriptive statistics of all the variables.

| Variables | Variables name          | Units  | Mean   | SD    | Max   | Min   |
|-----------|-------------------------|--------|--------|-------|-------|-------|
| lnAP      | Air pollution           | ug/m$^3$ | 4.0289 | 0.1869 | 4.5326 | 3.5351 |
| lnES      | Energy structure        | %      | 3.383  | 1.4010 | 4.6134 | -0.1393 |
| lnPGDP    | Per capita GDP          | RMB    | 11.5159 | 0.7151 | 13.2144 | 10.2470 |
| ln$^2$PGDP| Square of per capita GDP| RMB    | 133.1217 | 16.8184 | 174.6204 | 105.0010 |
2.3. Spatial models construction

Based on EKC hypothesis proposed by Grossman and Krueger (1991) [7], which an inverted U-shaped relationship between economic development and environmental pollution, we construct spatial panel models. Learning from the EKC theory and the general equilibrium model advanced by Antweiler et al. (2001) [8], the basic model can be constructed as follows:

$$\ln \text{AP}_{it} = \alpha_0 + \alpha_1 \ln \text{PGDP}_{it} + \alpha_2 \ln^2 \text{PGDP}_{it} + \alpha_3 \text{ES}_{it} + \epsilon_{it}$$  \hspace{1cm} (1)$$

According to Anselin (1995) [9], we construct two kinds of spatial panel models, including Spatial Lag Model (SLM) and Spatial Error Model (SEM), to explore the effect of energy structure on air pollution from 2010 to 2016 in GBA, the SLM and SEM are constructed as follows:

$$\ln \text{AP}_{it} = \alpha_0 + \rho \sum_{j=1}^{n} W_{ij} \ln \text{AP}_{jt} + \alpha_1 \ln \text{PGDP}_{it} + \alpha_2 \ln^2 \text{PGDP}_{it} + \alpha_3 \text{ES}_{it} + \epsilon_{it}$$  \hspace{1cm} (2)$$

$$\ln \text{AP}_{it} = \alpha_0 + \alpha_1 \ln \text{PGDP}_{it} + \alpha_2 \ln^2 \text{PGDP}_{it} + \alpha_3 \text{ES}_{it} + \mu_{it}$$  \hspace{1cm} (3)$$

Where i and t denote city and year respectively; AP represents the annual average values of PM$_{10}$ concentrations, PGDP denotes the per capita GDP, ES denotes energy structure. $\sum_{j=1}^{n} W_{ij} \ln \text{AP}_{jt}$ is spatial lag variable; $\rho$ denotes the spatial lag coefficient, indicating the spatial spillover effects of neighboring cities to local cities; W is spatial spatial weight matrix; $\epsilon$ is the random error vector; $\mu_{it}$ is equal to $\lambda \sum_{j=1}^{n} W_{ij} \mu_{jt} + \epsilon_{it}$, which $\lambda$ denotes the spatial error coefficient; $\alpha_0$ denotes individual fixed effect.

3. Results and discussions

3.1. Temporal and spatial distribution characteristics of air pollution

Table 2 lists air pollution distribution situation for 11 cities in GBA from 2010 to 2016. It shows that air pollution exists a downward trend from 2010 to 2016. Air pollution in Foshan city is the most serious, which reaches a maximum of 77 ug/m$^3$ in 2010, and years values are higher than 53 ug/m$^3$. Secondly, followed by Zhaoqing city, where PM$_{10}$ values are greater than 57 ug/m$^3$, and also reaches a maximum of 77 ug/m$^3$ in 2010 and 2011. The air pollution level of Zhuhai, Shenzhen, Hong Kong is not too serious compared with Foshan, Zhaoqing, Dongguan, Jiangmen, etc. Therefore, cross-regional environmental governance is an urgent task.

| Cities    | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|-----------|------|------|------|------|------|------|------|
| Dongguan  | 65   | 69   | 59   | 62   | 60   | 52   | 51   |
| Foshan    | 93   | 86   | 76   | 76   | 67   | 56   | 53   |
| Guangzhou | 66   | 62   | 62   | 62   | 57   | 52   | 50   |
| Huizhou   | 60   | 67   | 54   | 61   | 55   | 44   | 42   |
| Jiangmen  | 58   | 56   | 58   | 75   | 64   | 55   | 53   |
| Shenzhen  | 58   | 56   | 48   | 57   | 52   | 46   | 39   |
| Zhaoqing  | 77   | 77   | 54   | 76   | 74   | 58   | 57   |
| Zhongshan | 65   | 66   | 58   | 67   | 51   | 47   | 42   |
| Zuhai     | 60   | 52   | 49   | 60   | 49   | 43   | 40   |
| Hong Kong | 48   | 53   | 45   | 50   | 45   | 42   | 34   |
| Macao     | 56   | 59   | 53   | 54   | 53   | 52   | 46   |

Figure 2 shows the spatial quartile maps of air pollution in 2010, 2013 and 2016. It suggests that Zhaoqing, Foshan, Jiangmen’s air pollution level are the best serious in GBA, and always locate in the first echelon. Dongguan and Hong Kong are in the second and fourth echelon in the three years, respectively. Zhongshan retires from the second echelon in 2010 and 2013 to the second echelon in 2016. It is worth noting that Zuhuai’s air pollution level decreased in this three years, from the third echelon in 2010 to the second echelon in 2013, then to the first echelon in 2016. On the whole, the spatial distribution of air pollution in GBA exist agglomeration characteristics, the more serious cities are located in Zhaoqing, Foshan, Jiangmen and Dongguan, etc.
Figure 2. Spatial quartile maps of air pollution in 2010, 2013 and 2016.

Referring to the standard empirical method of spatial econometrics, this paper uses Moran’s I values to express the spatial correlation degree of air pollution. The Moran’s I values are calculated for air pollution from 2010 to 2016 by Geoda software, and Table 3 displays the Moran’s I values of air pollution in GBA. The global Moran’s I values are all significantly positive at the 10% significance level, except for 2011, which indicate that air pollution of most cities in GBA exists spatial correlation and obvious path dependence characteristics in their geographical distribution.

Table 3. Moran’s I values of air pollution in GBA from 2010 to 2016.

| Years | Moran’s I | E(I) | Sd(I) | P values |
|-------|-----------|------|-------|----------|
| 2010  | 0.3549    | -0.1000 | 0.2658 | 0.0481   |
| 2011  | 0.2099    | -0.1000 | 0.2882 | 0.1464   |
| 2012  | 0.3436    | -0.1000 | 0.2687 | 0.0471   |
| 2013  | 0.6575    | -0.1000 | 0.2977 | 0.0082   |
| 2014  | 0.6796    | -0.1000 | 0.2921 | 0.0043   |
| 2015  | 0.4624    | -0.1000 | 0.3066 | 0.0415   |
| 2016  | 0.5814    | -0.1000 | 0.2987 | 0.0118   |

3.2. Spatial estimation test of energy structure and air pollution in GBA

Before performing spatial measurement analysis, spatial models need to be selected. Based on the spatial measurement model selection decision rules proposed by Anselin (2005) [10]. Firstly, spatial correlation of the research object is judged by the Moran’s I value, and then by observing LM-Lag value and the LM-Error value to determine which model is more suitable. If the LM-Lag value and the LM-Error value are similar and significant, the Robust LM-Lag value and the Robust LM-Error value are further observed. Table 4 shows that the Moran’s I value is 0.4596, which is significant at the 1% level, indicating that there is a spatial correlation for air pollution in GBA. So, the OLS estimation results without considering spatial effects are biased and non-uniform. At the same time, the LM-Lag value and the LM-Error value are 30.2499 and 20.4127, respectively, both of which are significant at the 1% level. The Robust LM-Lag value is 16.6663, passing the 1% significance level test, and the Robust LM-Error value is also tested by the 1% significance level. Therefore, Spatial Dubin Model is more suitable.

Table 4. Spatial autocorrelation test of air pollution

| Test             | Index/degree of freedom | Statistics | P values |
|------------------|-------------------------|------------|----------|
| Moran's I        | 0.4596                  | 4.7371     | 0.0000   |
| LM-Lag           | 1                       | 30.2499    | 0.0000   |
| Robust LM-Lag    | 1                       | 16.6163    | 0.0000   |
| LM-Error         | 1                       | 20.4127    | 0.0000   |
| Robust LM-Error  | 1                       | 6.7792     | 0.0090   |

We find that fixed effect model is suitable through Hausman test. In order to overcome the bias of the estimation results caused by traditional OLS regression method without solving the endogenous problem, this paper use Spatial Dubin Model to examine the effect of energy structure on air pollution in GBA by Matlab software, and the estimation results are showed in Table 5. It can be seen from Table 5 that the coefficient of energy structure is positive, and the 1% significance level means that the coal
consumption ratio increases by 1%, and the air pollution index increases by 0.1381%. On the one hand, energy structure index directly reflects the industrial energy consumption structure; on the other hand, it reflects the energy consumption structure indirectly, indicating that the industrial energy consumption structure and energy consumption structure are positively correlated with air pollution, and the correlation is very high. The coefficient of per capita GDP is -1.2066, and the coefficient of square of per capita GDP is 0.0578, which proves that a “U”-type relationship exists between per capita GDP and air pollution. That is, with the continuous increase of per capita GDP, air pollution index first drops, and after reaching a certain threshold, it begins to rise.

Table 5. Spatial Durbin Model estimation results

| Variables     | Coefficient | Asymptot t-stat | z-probability |
|---------------|-------------|-----------------|---------------|
| lnES          | 0.1381      | 3.6077          | 0.0003        |
| lnPGDP        | -1.2066     | -1.4575         | 0.1449        |
| ln²PGDP       | 0.0578      | 1.6071          | 0.1080        |
| W*lnEC        | 0.2620      | 4.5852          | 0.0000        |
| W*lnPGDP      | -7.5295     | -2.6958         | 0.0070        |
| W*ln²PGDP     | 0.3470      | 2.8045          | 0.0050        |
| W*dep.var     | -0.2361     | -1.9107         | 0.0560        |
| R-squared     |             |                 |               |
| Corr-squared  |             |                 |               |

In order to explain the regression coefficient of spatial lag term of Spatial Durbin Model specifically, this paper decomposes the total effect of spatial spillover into direct effect and indirect effect by the partial differential method. The indirect effect reflects the influence of interpretative variables on the interpreted variables in a city. From the direct effect point of view, the energy structure has an impact coefficient of 0.1396 on air pollution, and passes the 1% significance level, indicating that the energy structure has a significant effect on air pollution. For indirect effect, the spatial spillover of energy structure is negative, indicating that energy structure of one city has an inhibitory effect on air pollution in other cities. Meanwhile, the direct effect of per capita GDP presents a “U”-type relationship, and the indirect effect presents an inverted “U”-type relationship.

Table 6. Direct effect, indirect effect and total effect of Spatial Durbin Model

| Variables     | Direct effect | Indirect effect | Total effect |
|---------------|---------------|-----------------|--------------|
| lnES          | 0.1396***     | -0.0285         | 0.1111***    |
|               | (3.7046)      | (-1.7381)       | (3.6023)     |
| lnPGDP        | -1.2060       | 0.2432          | -0.9628      |
|               | (-1.4506)     | (1.1195)        | (-1.4216)    |
| ln²PGDP       | 0.0578        | -0.0117         | 0.0461       |
|               | (1.5943)      | (-1.1955)       | (1.5615)     |

Note:*** indicates significance at the 1% level. Figures in parentheses are probability statistics.

4. Conclusions

Based on the panel data of 11 cities in GBA from 2010 to 2016, this paper uses spatial data analysis method to study the temporal and spatial distribution characteristics of air pollution. The results show that the more serious air pollution is mainly distributed in Zhaoqing, Foshan, Jiangmen, etc. Air pollution has spatial correlation and obvious “path dependence” characteristics in spatial distribution. Secondly, this paper further tests the spatial impact of energy structure on air pollution in GBA, and finds that the energy structure coefficient is positive, which means that the coal consumption increases 1%, the air pollution index will rise by 0.1381%. At the same time, the coefficient of per capita GDP is positive and the coefficient of square of per capita GDP is negative, which proves that a “U”-type relationship exists between per capita GDP and air pollution. Based on the above conclusions, the following suggestions are proposed. From a short-term perspective, air pollution reduction and effective
pollution control are effective ways, and changing the energy consumption structure in industrial development is the key to pollution control in the long run. When environmental pollution is being treated, cooperation among different cities should be actively pursued, and the spatial linkage of policy measures should be emphasized. In order to achieve sustainable development, developing tertiary industry, transforming economic growth mode, optimizing the industrial structure are necessary. At the same time, we must make full use of the technology spillover effects generated by foreign investment. In addition, the governments need to increase investment, especially the research and development investment of new energy technologies, and encourage and support the development of new energy technologies through market incentives.

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