The determinants of energy consumption in China: a spatial panel data approach

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Abstract. As the second largest country of energy consumption around the world, China is facing an increasing pressure on energy-saving and emission-reduction. However, there is little research to study the spatial features and determinants of China's energy consumption. This paper uses province level data in China from 2006 to 2016, and spatial panel model to analyze the determinants of energy emissions in China. The results indicate that the provincial energy consumption has a certain spatial autocorrelation, however, which is not strong. Regression results show that industrial development, economic level and financial development have significantly positive effects on energy consumption.

1. Introduction
In the past, Chinese economy has developed rapidly, with an average annual GPD growth of 8%. However, this rapid growth is characterized by high investment, high energy consumption and high emissions [1]. High energy consumption causes excessive resources consumption, as well as environmental pressure [2]. China has now become the world's second largest energy consumer after the United States, and the government has been actively promoting energy-saving and emission-reduction measures since 2013 to ensure sustainable development [3]. These measures have gained some achievements in recent years, but the policy targets have not been reached [4]. Therefore, research of features and determinants on energy consumption still has importance.

Previous studies have explored factors that affect energy consumption, such as Jin Wei (2016) [5], Han Gang (2017) Yin (2015) [6,7]. Some papers used non-linear regression methods to examine heterogenous factors on energy emissions, such as Dou Ruixin (2016) [8] and Li Sufang (2019) [9]. Some of these papers examined regional differences in energy consumption. Traditional regression methods assume that the individuals are homogeneous, however, the regions in fact vary in China, which is more in line with the assumption of individual heterogeneity. Besides, the economic activities between regions in China have a strong correlation, that is, the economic activities of one region is likely to be affected by the economic activities of the adjacent regions. Therefore, this paper adapts spatial econometric approach to examine the factors affecting energy consumption.
2. Methodology

2.1. Spatial weight construction
In order to examine the spatial relation on energy emissions between provinces, the paper constructs a binary spatial weight matrix. The paper has assumed that influences on energy consumption are geographically adjacent, and for simplicity, so the binary spatial weight matrix $W_n$ (the matrix is an $n \times n$ square matrix) is constructed as below, where $i$ and $j$ denote the province individuals.

$$\omega_{ij} = \begin{cases} 1 & \text{if } i \text{ and } j \text{ is adjacent} \\ 0 & \text{if } i \text{ and } j \text{ is not adjacent} \end{cases}$$

2.2. Spatial autocorrelation analysis
The global spatial autocorrelation can test the degree of correlation of the attribute among areas on the whole. The article uses the global Moran’s index to examine whether there is a regional autocorrelation in energy consumption globally. The index is calculated as follow:

$$\text{Moran } I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} (Y_i - \bar{Y})(Y_j - \bar{Y})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij}}$$

Where $Y_i$ is the energy consumption amount of the province, $\omega_{ij}$ denotes the elements in spatial weight matrix $W_n$, and $n$ is the number of provinces. Moreover, $S^2 = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \bar{Y})^2$ and $\bar{Y} = \frac{1}{n} \sum_{i=1}^{n} Y_i$. The value of the index will be between -1 and 1. The index closer to 1, the positively stronger the spatial autocorrelation is. That is, one region of high energy consumption has adjacent regions of high energy consumption. The index close to -1 indicates negatively spatial autocorrelation. If the index is close to 0, it indicates that energy consumption has no spatial autocorrelation.

Further, the Moran’s index scatter plot can be drew by calculating the standardized attributes and spatial lag standardized attributes of each individual. The scatter plot will be divided into four quadrants. The first quadrant represents a high-high positive relationship, the third quadrant represents a low-low positive correlation, and the other quadrants represent a negative correlation. By observing the number of individuals falling into different quadrant, the spatial correlation of energy consumption can be further understood.

2.3. Spatial Panel Model
Elhorst (2012) [10] raises two main types of spatial panel models, namely the spatial lag panel model (SLM) and the spatial error panel model (SEM). The spatial lag panel model mainly examines whether the dependent variable will be affected by adjacent individuals, and the spatial error panel model mainly examines whether spatial correlation exists in the error terms. Because the paper expects to investigate the spatial features of energy consumption, so the spatial lag panel model is selected. Similarly, in terms of different assumptions of the panel model, the spatial panel model has fixed effects and random effects. Fixed effects can also be classified by time fixed effects, individual fixed effects and two-way fixed effects. In this paper, a fixed-effect model is selected, and different types of fix effects are presented for comparison. The spatial lag panel model is expressed as follows:

$$Y = \rho(I_n \otimes W_n)Y + \beta X + (T_n \otimes I_n)\mu + (I_n \otimes T_n)\delta + u$$

Among them, $Y$ is the $nt \times 1$ vector of dependent variables, $X$ is the $nt \times k$ matrix of independent variables, and $k$ is the number of independent variables; $\otimes$ is Kronecker product. $(I_n \otimes W_n)Y$ denotes the dependent variable multiplied by the spatial weight matrix and is called the
The coefficient $\rho$ is used to measure the influence of the adjacent $Y_{j,i}$ on local $Y_i$. The $\mu$ and $\delta$ denote the individual and time effects, respectively. $u$ denotes the error terms.

On the basis of the spatial lag panel model, the spatial lag term $(I_i \otimes W_{ni})X$ of the independent variables can also be added to examine the influence of the independent variables $X_{j,i}$ of adjacent individuals on the local $Y_i$. The corresponding model is called a spatial dubin model and is expressed as follows

$$Y = \rho(I_i \otimes W_{ni})Y + \beta X + \gamma(I_i \otimes W_{ni})X + (T_i \otimes I_n)\mu + (I_i \otimes T_n)\delta + u$$

### 3. Data

The article uses panel data of 30 provinces in China from 2006 to 2016 to study the determinants of energy emissions. Because energy emissions data of Tibet is missing, Tibet was not considered and the final number of the sample is 330. The energy emissions data comes from the China Energy Yearbook. Other data including province level GDP, population, amount of bank loans, secondary industry add value, and FDI amount are from China Statistical Yearbook.

The paper examines the determinants of energy consumption in three aspects: energy consumption features, economic development and finance level. Energy consumption feature is examined by energy consumption structure and industry production structure. Economic development is examined by GDP per capita and urbanization level. And finance level is examined by financial development and foreign direct investment.

The variables are constructed as follow: (1) ENGpc is the energy consumption per capita, which is energy consumption amount divided by provincial population; ENGstr denotes the energy consumption structure, which is the coal consumption divided by the total energy consumption; Str denotes the industry production structure, which is the province's secondary industry add value divided by GDP; (2) GDPpc is the GDP per capita, and Urban denotes the urbanization, which is obtained by dividing the urban population by the total population of the province; (3) FIN is the financial development, which is the total loan amount from bank divided by the total GDP, and FDI is the amount of foreign direct investment.

This paper selects the energy consumption per capita as the dependent variable, and the other variables are independent variables. All variables will be logarithm when used in regression. Table 1 are the statistics summary of all the variables:

| variable   | Description                        | N  | mean  | sd    |
|------------|------------------------------------|----|-------|-------|
| ENGpc      | Energy Consumption per capita (tons)| 330| 3.305 | 1.525 |
| ENGstr     | Energy Structure (%)               | 330| 0.958 | 0.381 |
| Str        | Second Industry Ratio (%)          | 330| 0.472 | 0.08  |
| GDPpc      | GDP per capita (yuan)              | 330| 3846  | 22.61 |
| Urban      | Urbanization Rate (%)              | 330| 0.529 | 0.138 |
| FIN        | Finance Development (%)            | 330| 1.119 | 0.364 |
| FDI        | Foreign Direct Investment(million yuan) | 330| 6500  | 7200  |
4. Regression and discussion

4.1. Global Spatial Autocorrelation Test

Global Moran’s index of energy consumption measures the spatial autocorrelation of energy consumption, and all results are significant at the 90 percent interval. Overall, spatial correlation of energy consumption is not strong in provincial data. Since 2006, the global Moran’s index has been declining from 0.148 in 2006 to 0.067 in 2016. The results might be due to the implementation of energy-saving and emission-reduction policies by central government, which have positive influences on energy reduction in various provinces. Therefore, as each province reduces energy consumption, the spatial autocorrelations have fallen.

In the Moran’s index scatter plot, it can be observed that most points fall in the first and the third quadrants. The scatter plot indicates energy consumption has positive spatial correlation.

![Figure 1. Global Moran’s I for provincial energy consumption in 2006-2016.](image1)

4.2. Spatial Panel Regression

The paper uses the spatial Dubin panel model and spatial lag panel model to examine the determinants of energy consumption per capita. The results of the three types of fixed effects for each model are also reported in Table 2.

It can be observed that the energy structure and ratio of secondary structure has a positive effect on energy consumption per capita. These results indicate that by increasing the proportion of coal consumption and industrial production, energy consumption will increase. And the results also assume that the increase in energy consumption could be caused by industrial production. In the past few decades, China has developed industrialization rapidly in a way of high energy consumption and high emissions, which have led to excessive energy consumption, and which have strengthened the coal-
dependent energy structure. If China needs to achieve policy target of energy-saving and emission-reduction, the future policy should focus on adjustment on industrial structure and on industrial innovation, to deviate from current coal-dependent energy consumption. In addition, we can observe that GDP per capita and urbanization also have positive effect on energy consumption per capita. These results indicate that the energy consumption would increase as the overall economy develop. With the increase in income per capita and the expansion of urbanization, people's living standards will continue to improve, so people will choose lifestyles with higher energy consumption, such as owning private cars or building larger and higher buildings. Finally, we can see that the level of financialization and foreign direct investment have positive influence on energy consumption per capita. Chinese industrial enterprises are mainly financed by loans from banks, and partly by foreign direct investment. Therefore, when bank loans increase and foreign direct investment increases, it will promote the development of industry, and then increase energy consumption.

Table 2. Results of determinants on energy consumption.

| Main       | Individual effect | Time effect | Both      | Spatial Dubin Panel Model | Spatial Lag Panel Model |
|------------|------------------|-------------|-----------|---------------------------|------------------------|
| lnENGstr   | 0.170***         | 0.306***    | 0.150***  | lnENGstr                  | 0.232***               |
|            | (0.00)           | (0.00)      | (0.00)    | (0.00)                    | (0.00)                 |
| lnStr      | 0.202***         | 0.0860      | 0.236***  | lnStr                     | 0.163***               |
|            | (0.00)           | (0.19)      | (0.00)    | (0.00)                    | (0.00)                 |
| lnGDPpc    | 0.0590           | 0.224***    | 0.133***  | lnGDPpc                   | 0.251***               |
|            | (0.18)           | (0.00)      | (0.00)    | (0.00)                    | (0.00)                 |
| lnUrban    | 0.555***         | 0.855***    | 0.537***  | lnUrban                   | 0.235***               |
|            | (0.00)           | (0.00)      | (0.00)    | (0.00)                    | (0.00)                 |
| lnFIN      | 0.017***         | -0.104**    | 0.019***  | lnFIN                     | 0.031***               |
|            | (0.01)           | (0.00)      | (0.00)    | (0.00)                    | (0.00)                 |
| lnFDI      | 0.217**          | 0.243       | 0.230**   | lnFDI                     | 0.245**                |
|            | (0.04)           | (0.18)      | (0.02)    | (0.01)                    | (0.78)                 |
| Wx         |                  |             |           |                           |                        |
| lnENGstr   | -0.172***        | 0.204**     | -0.208**  |                           |                        |
|            | (0.00)           | (0.02)      | (0.00)    |                           |                        |
| lnStr      | 0.0570           | 0.140       | 0.348***  |                           |                        |
|            | (0.38)           | (0.24)      | (0.00)    |                           |                        |
| lnGDPpc    | 0.264***         | -0.328*     | 0.448***  |                           |                        |
|            | (0.00)           | (0.07)      | (0.00)    |                           |                        |
| lnUrban    | -0.438***        | 0.516***    | -0.241**  |                           |                        |
|            | (0.00)           | (0.00)      | (0.01)    |                           |                        |
| lnFIN      | 0.079***         | -0.064**    | 0.085***  |                           |                        |
|            | (0.00)           | (0.01)      | (0.00)    |                           |                        |
| lnFDI      | 0.310*           | -1.693**    | 0.0580    |                           |                        |
|            | (0.09)           | (0.00)      | (0.76)    |                           |                        |
| Spatial rho| 0.431***         | 0.233***    | 0.227***  |                           |                        |
|            | (0.00)           | (0.00)      | (0.00)    |                           |                        |
| Spatial rho|                  |             |           |                           |                        |
|            | 0.253***         | 0.253***    | 0.237***  |                           |                        |
|            | (0.00)           | (0.00)      | (0.00)    |                           |                        |
| N          | 330              | 330         | 330       |                           |                        |
| r2         | 0.189            | 0.479       | 0.237     |                           |                        |

Numbers in the parentheses represent p-values
* P<0.1; ** P<0.05; *** P<0.01
5. Conclusions

This paper uses spatial panel approach to analyze the spatial features and determinants of energy emissions with province level panel data from 2006 to 2016. The results of spatial autocorrelation analysis show that energy emissions are spatially related, but the autocorrelation is not strong. The spatial panel regression results show that spillover effect of energy emissions exists among provinces. When the level of industrial development, economic development, and financial development increases, the energy consumption per capita also increases, indicating that China's energy consumption level is mainly boosted by economic development.

Based on the above conclusions, two policy suggestions are put forward: (1) Enterprise need to establish environmental protection awareness and actively respond to save resources in production. (2) At present, energy consumption is still dependently high-pollution and high-energy emission. Attention should be paid to research and development of new energy sources.

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