Analysis of carbon emission and its influencing factors

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Abstract: Based on the 2000-2015 data of 30 provinces in China, this paper discusses the total population, per capita GDP and the influence of the energy intensity of carbon emissions, using the IPCC provides the calculation method of the carbon emissions, the STIRPAT model and Spatial Dubin model,.The results show that firstly , the change trend of carbon emissions in 30 provinces in China is affected by the carbon emissions of neighboring provinces, i.e. there is spatial autocorrelation. Secondly, the use of Spatial Dubin model to estimate the population, the per capita GDP and energy intensity has a significant influence on carbon emissions. Thirdly, the variables of this province and adjacent provinces of carbon emissions have a positive effect, energy intensity is the most important factors affecting carbon emissions.

1. Introduction

Global warming has been a hotspot of the world's response to global warming, and human economic behavior has caused a lot of greenhouse gas emissions to be the key factor in the warming of the climate[1]. At present, the global climate change problem is one of the most important factors affecting the economic and social development of the future and the restructuring of the global political and economic pattern[2]

The current research has been recognized as a factor in the impact of carbon emissions in the areas of population, economic development, and technological progress. Firstly, the decisive control of the population on the emission of carbon is the first to bring about the attention of the academic community [3], and the problems such as food security, water pollution, energy and traffic pressure caused by the growth of the population will negatively impacton the environment [4]. Secondly, the economic development level and regional carbon emissions in terms of regional GDP per capita, in part of the region, are the Environmental Kuznets curve[5-8], which is the Environmental Kuznets curve, which means that the growth of carbon emissions is going to slow down to a certain extent with the development of the economy. Thirdly, technological progress level is the most important factor to restrain carbon emissions [9]. A lot of research has shown that a different level of technology in the region is a key cause of energy efficiency and efficiency [10].

2. Data and models

2.1 Carbon emission calculation method

The process is divided into three steps: the amount of energy consumption in the energy balance is converted into a standard quantity. Convert standard amounts of various energy sources into carbon emissions (excluding electricity and heat). When calculating power and thermal energy consumption produces carbon emissions, it is measured in physical quantities.

Use the following formula to calculate:

$$C_{it} = \sum_{j=1}^{17} Z_{ijt} + O_{it} + I_{it}$$

$$= \sum_{j=1}^{17} ZE_{ijt} \times \delta Z_{ijt} \times \eta Z_{ijt} + OE_{it} \times \eta O_{it} + IE_{it} \times \eta I_{it} \qquad (1)$$

where:

$$\delta Z_{ijt} = \frac{ZEB_{jt}}{ZES_{jt}} \qquad (2)$$

In equation (2) the δZ_{ijt} is the standard conversion coefficient of final energy consumption. As can be seen from equation (1), the standard conversion coefficient is the same for different i every year. ZEB_{jt}、ZES_{jt} is the standard amount and the actual amount of energy consumption of type j energy terminal of t.

2.2 Analysis of China's carbon emission status

As can be seen from figure 1.,from 2000 to 2013, China's total carbon emissions showed a significant upward trend, with a total increase rate of 284%. From 2013 to 2015, China's total carbon emissions have gradually stabilized in the region. The growth rate of China's carbon emissions from 2000 to 2015 has been declining. It is worth noting that the growth rate of China's carbon emissions has been negative since 2014, indicating that China's energy-saving and emission reduction measures have had a good effect on environmental pollution.
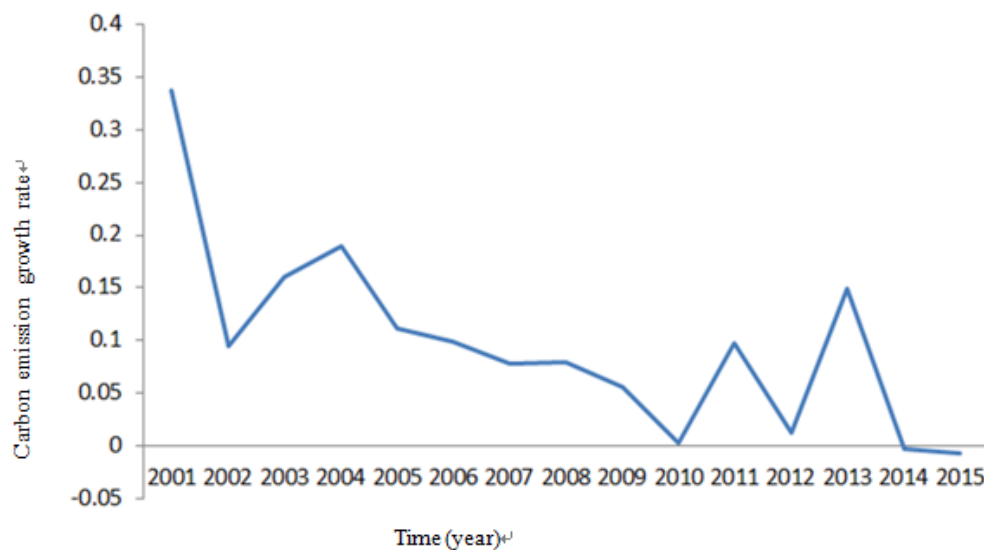

Figure 1. China's carbon emission growth rate from 2000 to 2015

3. Empirical analysis

3.1 STIRPAT Model

Dietz and Rosa[11] proposed the STIRPAT model based on the traditional model IPAT, and its general form is:

$$I = aP^b A^c T^d e \qquad (3)$$

Where, the constant a is the model coefficient, environmental pressure (I), where b、c、d is the driving index of population factor (P), affluence factor (A) and technology level factor (T), and e is the random error term of the model.

Take the right and left side of equation (3) as logarithm, respectively

$$lnI = \ln a + b\ln(P) + c\ln(A) + d\ln(T) + \ln e \tag{4}$$

In equation(4)，$\ln(I)$ is the dependent variable of the model, $\ln(P)$、$\ln(A)$、$\ln(T)$ is the independent variable of the model, and $\ln a$、$\ln e$ is the constant term and error term of the model respectively. Using the concept of elastic coefficient, it can be known that when P、A、T changes by 1% respectively, it will cause the change of $b\%$、$c\%$、$d\%$ in I.

3.2 Spatial correlation test

In this paper, the Moran's I index was used to test the spatial autocorrelation of the total carbon emissions of 30 provinces in China. Formula (5) for its expression.

$$Moran's\ I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}(X_i - \overline{X})(X_j - \overline{X})}{\sum_{i=1}^{n}(X_i - \overline{X})^2} \tag{5}$$

The closer the I value is to 1, the stronger the spatial positive correlation is, and the closer the I value is to -1, the stronger the spatial negative correlation is. From the results of the test, the value of "I" is at a significant level of 5%, which means that the total amount of carbon emissions in each province is significant. The self-correlation detection results in this paper are shown in table 1.

Table 1 Spatial autocorrelation test results

Year	Moran's I values	P values	Expect	Mean	Standard deviation
2000	0.265	0.011	-0.033	-0.029	0.116
2001	0.147	0.031	-0.033	-0.018	0.095
2002	0.303	0.001	-0.033	-0.034	0.113
2003	0.261	0.010	-0.033	-0.030	0.114
2004	0.289	0.011	-0.033	-0.031	0.120
2005	0.264	0.009	-0.033	-0.028	0.113
2006	0.285	0.007	-0.033	-0.028	0.117
2007	0.101	0.008	-0.033	-0.035	0.050
2008	0.273	0.004	-0.033	-0.035	0.116
2009	0.250	0.004	-0.033	-0.036	0.105
2010	0.268	0.014	-0.033	-0.022	0.114
2011	0.255	0.011	-0.033	-0.031	0.115
2012	0.234	0.011	-0.033	-0.038	0.115
2013	0.234	0.025	-0.033	-0.029	0.119
2014	0.201	0.002	-0.033	-0.037	0.117
2015	0.234	0.011	-0.033	-0.031	0.112

3.2.1 Establishment and selection of spatial measurement model

The standard equation only considers the action mechanism of various factors on industrial structure upgrading, without considering the influence of spatial effect. In fact, ignoring spatial factors will lead to bias in model setting and eventually lead to misjudgment of results [12,13]. Anselin[14](1988) introduced the spatial measurement method, which included spatial dependence and heterogeneity in the estimation equation to avoid such errors in the model. In this paper, on the

basis of industry structure standard equation, integration with space panel model to analyze the influence of the selected factors on the spatial and temporal pattern changes of the industrial structure, this needs to add the item [15] to characterize the spatial lag or spatial error in the standard equation (1). This paper mainly considers three common spatial econometric models. Different models correspond to different ways of setting interaction effects. The specific expression is shown in formula (6), formula (7) and formula (8) .

(1) Spatial Autoregressive Model, SAR:

$$Y_{it} = \alpha + \rho \sum_{j=1, j\neq i}^{N} W_{ij} Y_{jt} + \beta X_{it} + \mu_i + \nu_t + \mu_{it} \tag{6}$$

(2) Spatial Error Model, SAR:

$$\begin{cases} Y_{it} = \alpha + \beta X_{it} + \mu_i + \nu_t \\ \varepsilon_{it} = \phi \sum_{j=1, j\neq i}^{N} W_{ij} \varepsilon_{it} + \mu_{it} \end{cases} \tag{7}$$

(3) Spatial Dubin Model, SDM:

$$Y_{it} = \alpha + \rho \sum_{j=1, j\neq i}^{N} W_{ij} Y_{jt} + \beta X_{it} + \theta \sum_{j=1, j\neq i}^{N} W_{ij} X_{jt} + \mu_i + \nu_t + \mu_{it} \tag{8}$$

Where, the subscript i, j represents the region, and the subscript t represents the time. Y_{it} is the total carbon emission of the region in time t; X_{it} is the population (P), affluence (A) and technology (T) factors of the region in time; ε_{it} is random disturbance term; μ_i and ν_t are respectively regional and time effects. W_{ij} is the weight matrix of economic distance [12].

The spatial durbin model is constructed, and the original hypothesis H_0^1 is established: spatial durbin model can be transformed into the spatial lag model; H_0^2: spatial dubin model can be transformed into spatial error model. The test results are shown in table 2. The results show that both of the above hypotheses are rejected, so the spatial dubin model should be chosen.

Table 2 LR and Wald test results

Test	Statistic	P values
LR-lag	35.009	0.000
LR-err	67.321	0.000
Wald-lag	39.004	0.000
Wald-err	77.231	0.000

The spatial durbin model can be divided into spatial durbin model under fixed effect and spatial durbin model under random effect. The test results table 3 show that the spatial durbin model under fixed effect is established under 1% significance level.

Table 3 Hausman test results

Test	Statistic	P values
Hausman	472.012	0.000

3.2.2 Estimation of spatial econometric model

According to the estimation results, the regression coefficient of SDM model is significantly positive at the level of 1%, which indicates that the dependent variable has an important influence on

the independent variable. The regression coefficient of the spatial lag term is also significantly positive at the level of 1%, which indicates that the neglected spatial effect is of great significance to the study of carbon emissions. In Table 4，for the OLS model, the P value of the affluence factor (A) is not significant, and the goodness of fitting is less than that of SDM model.

If the spatial lag term is not included, the regression coefficient can reflect the direction and magnitude of the influence of independent variables on dependent variables. If the spatial lag term is included, the regression coefficient can only judge the influence of independent variables on the direction of dependent variables. Direct effect refers to the average effect of explained variables on explanatory variables in the region, indirect effect refers to the average effect of explained variables on explanatory variables in neighboring provinces, and total effect refers to the average effect of explained variables on overall explanatory variables. The results of the decomposition of direct and indirect effects of population (P), per capita GDP (A), energy intensity (T) are shown in table4.

(1) Direct effects: from the perspective of the direct effect of the spatial doberman model, the energy intensity of carbon development an important role in the province, is the first major influence factors affect its carbon emissions, the population is the influence of provincial secondary influence factors of carbon emissions.

(2) Iindirect effect: from the indirect effect of spatial dubin model, the total population (P) and energy intensity (T) both passed the significance test of 1%. In the case of significance of 10%, the benefit effect of per capita GDP (A) on neighboring areas was not significant. Under the indirect effect, energy intensity is still the biggest factor affecting carbon emissions.

Based on the results of the direct effects and the indirect effects, energy intensity is the primary factor in reducing carbon emissions in the provinces and neighboring provinces. It means that to improve environmental pollution, to reduce carbon emissions, to reduce carbon emissions at the same time as economic growth, we must vigorously develop science and technology.

Table 4 Direct effect, Indirect effect and Total effect

Variable	Direct effect	Indirect effect	Total effect
ln(P)	1.011*** [0.000]	0.187*** [0.000]	1.112*** [0.000]
ln(A)	0.852*** [0.000]	0.116 [0.114]	0.871*** [0.000]
ln(T)	1.014*** [0.000]	0.243*** [0.000]	1.263*** [0.000]

Note: *, ** and *** respectively represent significant levels of 10%, 5% and 1%.

4. Conclusion and policy advice

Until 2015, the eastern region of carbon emissions is higher than the less developed areas in the Midwest. The carbon intensity of the Chinese provinces and cities is high in the Midwest, and the east coast is low.

A spatial correlation check was conducted using Moran 'I value, which was greater than zero at a level of significantly 5 %, indicating positive correlation of total carbon emissions in each province. The total population (P), per capita GDP (A) and energy intensity (T) all have positive effects on the total carbon emissions at the significance level of 1%. From the total effect of the space dubin, the energy intensity has the most impact on carbon emissions, and the total population is second, and per capita GDP has the least impact on carbon emissions.

From the current trend of carbon emissions in every province in China, the future of China's carbon emissions is still rising. Therefore, the following Suggestions are proposed:

(1) At the significance level of 1%, the coefficient of energy intensity to the total carbon emission is significantly positive, and both direct and indirect effects are the first major factor affecting the production of carbon emissions, indicating that the reduction of energy intensity is the key to the

reduction of carbon emissions. The state should vigorously develop science and technology to improve energy efficiency.

(2) At the significance level of 1%, the coefficient of the total population to the total carbon emission is significantly positive, and both direct and indirect effects are the second major factor affecting the carbon emission. Therefore, China's population growth model should change from "quantitative" growth model to "qualitative" growth model.

(3) At the significance level of 1%, the coefficient of per capita GDP to total carbon emissions is significantly positive, and is the third factor under the direct effect. Economic growth will lead to an increase in carbon emissions. When economic growth reaches a certain level, economic development will inhibit the increase of carbon emissions. We should improve the quality of economic growth and strive to achieve coordinated economic and environmental development at an early date.

Under the circumstances of controlling carbon emissions from each province, China should also establish a regional cooperation mechanism, allowing the economically developed eastern coastal regions to help reduce carbon emissions in the western outback. On the other hand, in order to prevent a bad race between provinces, the Chinese government should be able to incorporate practical situations to encourage the provinces to develop and encourage the provinces to develop together.

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