

An Empirical Analysis on the Nonlinear Relationship Between Economic Growth and Carbon Dioxide Emissions in China

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ABSTRACT

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Based on the traditional theory of environmental Kuznets curve (EKC), this paper selects the panel data in 2000-2017 of 30 provincial administrative regions (provinces) in China as objects, and estimates the per capita carbon dioxide (CO₂) emissions of each province. On this basis, an EKC econometric model with spatial effect was established, and used to empirically analyze the nonlinear relationship between economic growth and CO₂ emissions. The main results are as follows: (1) The provinces differed greatly in per capita CO₂ emissions; the per capita CO₂ emissions of Inner Mongolia, Ningxia, Shanxi, Tianjin, and Liaoning were relatively high, while those of Hunan, Jiangxi, Guangxi, Sichuan and Hainan were relatively low. (2) In addition to obvious spatial correlation, the per capita CO₂ emissions of the provinces have spatial heterogeneity: most provinces belong to cluster areas, but only a few fall in the areas of spatial outliers. (3) The EKC spatial econometric model shows that the economic growth has a significant inverted U relationship with CO₂ emissions. In other words, with the growth in economy, the CO₂ emissions firstly increase and then decrease. (4) CO₂ emissions are clearly promoted by industrial structure, energy consumption structure and environmental regulation, but suppressed by the level of opening.

1. INTRODUCTION

Over the past four decades, the rapid economic growth is a mixed blessing to China. On the upside, a huge amount of economic wealth is accumulated; on the downside, lots of energy is consumed, emitting a massive amount of carbon dioxide (CO₂). According to statistics from Carbon Brief, China released a staggering amount of 9.8 billion tons of CO₂ in 2017, up by 1.7% from the amount of the previous year. In 2010, China surpassed the US for the first time as the largest carbon emitter in the world. Currently, the CO₂ emissions of China accounts for 28% of the global total, more than those of the US (14%) and the EU (12%) combined. The heavy CO₂ emissions intensify the greenhouse effect and seriously affect our daily lives. On the UN Climate Change Conference 2009 in Copenhagen, China promised to reduce the CO₂ emission per unit of gross domestic product (GDP) by 40-45% before 2020. To honor the promise, China must withstand a huge pressure on carbon reduction.

Meanwhile, China's economic growth is still featured by high investment, pollution and emissions, under the driving forces of investment and industrialization. These features are expected to remain for quite a long time. Therefore, it is a key issue for governments at all levels in China to strike a balance between economic growth and CO₂ emissions. In other words, the governments and the academia must work together to ensure the healthy development of national economy, while slashing CO₂ emissions. To formulate reasonable carbon reduction policies, the governments at all levels in China must explore deep into the following questions: What is the

relationship between economic growth and CO₂ emissions in China? Is it linear or nonlinear? What are the factors that affect CO₂ emissions, other than economic growth?

The relationship between economic growth and CO₂ emissions has long been a research hotspot. According to the relevant literature, there are four different conclusions about the relationship. Some scholars found that economic growth has a purely linear relationship with CO₂ emissions, i.e. CO₂ emissions continue to increase with the growth of economy [1, 2].

Some scholars held that economic growth has a typical nonlinear relationship with CO₂ emissions. The most popular theory is the environmental Kuznets curve (EKC). Proposed by Grossman and Krueger [3], the EKC theory describes the relationship between economic growth and CO₂ emissions as an inverted U curve. This description is widely received among scholars. For example, Lindmark [4], Nasir and Rehaman [5] established time series models for EKC-based empirical research, and validated the inverted U relationship between economic growth and CO₂ emissions in countries like Sweden, Pakistan and Spain. Through empirical analyses on China, Jalil and Mahmud [6], Du and Wei [7], Wang et al. [8], and Hu et al. [9] confirmed that the relationship between economic growth and CO₂ emissions in China also exhibits as an inverted U curve.

Some scholars illustrated the relationship between economic growth and CO₂ emissions as other types of curves. Dinda [10], McConnell [11], Stem [12], and Task and Zaim [13] suggested that the relationship between long-term economic growth and CO₂ emissions takes the form of an

inverted N curve, a positive N curve or an M curve, rather than the inverted U curve.

Some scholars argued that economic growth has nothing to do with CO₂ emissions. For instance, Wang [14] carried out an EKC-based analysis on the panel data in 1971-2007 of 98 countries, revealing that economic growth is not correlated with CO₂ emissions.

To sum up, Chinese and foreign scholars have explored deep into the relationship between economic growth and CO₂ emissions, especially from the angle of the EKC. However, there is a major defect with the EKC-based research: the traditional EKC theory assumes that regional CO₂ emissions are spatially independent of each other. In simple terms, the CO₂ emissions of a region have a significant impact on that region, but a negligible impact on the surrounding regions.

Anselin and Rey [15] clearly pointed out that all data are correlated in space, especially CO₂ emissions. As an important greenhouse gas (GHG), CO₂ naturally has a certain degree of spatial spillover. The spatial correlation of CO₂ emissions is enhanced by the pollution transfer policies between regions. Moreover, China is undergoing the rapid integration of regional economies. The spatial dependence between regions grows continuously, due to the environmental cooperation and technology diffusion across regions.

Therefore, the spatial correlation between regions must be considered before examining the relationship between economic growth and CO₂ emissions. Otherwise, there might be large errors in the research results. On this basis, this paper introduces the spatial correlation between regions to the empirical verification of the EKC assumption on the relationship between economic growth and CO₂ emissions.

2. METHODOLOGY

2.1 Estimation method for CO₂ emissions

The annual report from the World Bank shows that, in most countries, 70% of CO₂ emissions come from the consumption of fossil energy. The proportion is as high as 90% in China, for the energy structure is dominated by fossil energy like coal and petroleum. Since China's National Bureau of Statistics has not released the data on CO₂ emissions in each provincial administrative regions (hereinafter referred to as provinces), most Chinese scholars estimated CO₂ emissions based on the consumption of fossil energy [16]. Following this best practice, this paper estimates CO₂ emissions according to Section 6, Vol. 2 of the IPCC 2006 *Guidelines for National Greenhouse Gas Inventories*:

$$CO_2 = \sum_{i=1}^{14} E_i \times NCV_i \times CEF_i \times COF_i \times (44/12) \quad (1)$$

where, CO₂ is the CO₂ emissions to be estimated; *i* is the type of energy; *E* is the total consumption of all types of energies; *NCV* is the net calorific value of each type of energy; *CEF* is carbon emissions coefficient; *COF* is carbon oxidation factor of each type of energy; 44 and 12 are the molecular weights of CO₂ and carbon, respectively.

According to the consumption data released by China's National Bureau of Statistics, *i*=1, 2, ..., 14. Where, 1-14 represent coal, coke, coke oven gas, blast furnace gas, converter gas, other gases, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, natural gas and liquefied

natural gas, respectively. For simplicity, the consumptions of different types of energies, which are measured in different units, were converted by the standard coal coefficients (unit: 10,000 TCE) and added up to obtain the *E* value. The *NCV* was obtained by converting the consumption of each type of energy to the unit TJ.

2.2 Spatial autocorrelation coefficient and local indicators of spatial association (LISA)

This paper mainly examines the relationship between economic growth and CO₂ emissions. Here, CO₂ emissions specifically refer to the per capita CO₂ emissions in each province. To construct a robust EKC model, it is necessary to confirm whether the per capita CO₂ emissions of different provinces have significant spatial correlation (spatial dependence). The spatial correlation is a spatial attribute of per capita CO₂ emissions, that is, the clustering of provincial per capita CO₂ emissions in space. In other words, the per capita CO₂ emissions of neighboring provinces are highly similar, due to the spatial spillover effect.

Generally, spatial correlation is measured by the spatial autocorrelation coefficient: Global Moran's I [17]:

$$Moran's\ I = \frac{n}{\sum_{i=1}^n (x_i - \bar{x})^2} \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n W_{ij}} \quad (2)$$

where, *W_{ij}* is the spatial weight matrix consisting of zeros and ones; *x_i* and *x_j* are the observations of provinces *i* and *j*, respectively; $\bar{x} = (\sum x_i)/n$ is the mean observation of all provinces.

Global Moran's I generally falls within [-1, 1]. If the index is -1, the observations are completely negatively correlated in space; if the index is 1, the observations are completely positively correlated in space; if the index is 0, the observations are completely uncorrelated in space.

Once its value is determined, Global Moran's I must subject to authenticity test, using the Z-score normal distribution. The index will pass the authenticity test, if its value is significant on three levels: 10%, 5% and 1%. The Z-score can be expressed as:

$$Z(d) = \frac{[Global\ Moran's\ I - E(Global\ Moran's\ I)]}{\sqrt{VAR(Global\ Moran's\ I)}} \quad (3)$$

Global Moran's I demonstrates whether the provinces have spatial correlation in CO₂ emissions on the global scale, failing to reflect the spatial distribution of each province in local areas. To solve the problem, Local Moran's I, a.k.a. local indicators of spatial association (LISA), was introduced to disclose the distribution of each province in the four quadrants (H-H, L-H, L-L, H-L) of the spatial coordinate system [18]:

$$Local\ Moran's\ I = \frac{n^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \frac{(x_i - \bar{x}) \sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n W_{ij}} \quad (4)$$

2.3 EKC Theory

The relationship between economic growth and environmental pollution has always been in the limelight. In

1993, Grossman and Krueger proposed the EKC, attracting much attention from the academia. According to the EKC theory, a country or region has relatively light environmental pollution, when the economy just starts to develop. But as the economy takes off, both income and resource consumption will increase gradually, causing greater pollution to the environment. In this stage, economic growth is positively correlated with environmental pollution. With further growth in economy, the income will reach an inflection point or critical value. Then, people will realize the importance of environmental protection, and take multiple measures to curb the emissions of pollutants to the environment. In this stage, economic growth is negatively correlated with environmental pollution. Overall, the relationship between economic development and environmental pollution is not purely linear, but an inverted U curve.

The EKC theory confirms the existence of a long-term internal relationship between economic growth and environmental protection. But this does not necessarily mean that environmental quality will improve with the rising income. The government's economic measures or environmental policies also directly bear on the environment.

In the light of Grossman and Krueger [3] and Coal [19], the traditional EKC model between economic growth and environmental pollution can be expressed as:

$$Y = \beta_0 + \beta_1 x + \beta_2 x^2 + \mu \quad (5)$$

where, Y is the index of environmental pollution (e.g. per capita CO₂ emissions); x is the index of economic growth (e.g. per capita GDP); μ is a random perturbation; β_0 is a constant; β_1 and β_2 are the parameters of the first- and second-order terms of economic growth, respectively.

The relationship between environmental pollution and economic growth depends on the values of β_0 , β_1 and β_2 :

(1) If $\beta_0 \neq 0$ and $\beta_2 \neq 0$, there is a purely linear relationship between Y and x : with the growth in economy, environmental pollution either improves or worsens.

(2) If $\beta_1 > 0$ and $\beta_2 < 0$, there is an inverted U relationship between Y and x : as the economy starts to develop, environmental pollutants increase with the rapid economic growth; once the economy reaches an advanced level, pollutant emissions will drop with further economic growth. This relationship is the basic form of the EKC model.

(3) If $\beta_1 < 0$ and $\beta_2 > 0$, there is a U relationship between Y and x : as the economy starts to develop, economic growth alleviates environmental pollution; once the economy reaches an advanced level, economic growth causes environmental deterioration.

(4) If $\beta_0 \neq 0$ and $\beta_1 = 0$, there is no correlation between Y and x : economic growth has no impact on environmental pollution.

2.4 EKC spatial econometric model

In the traditional EKC model, the relationship between economic growth and environmental pollution is discussed under the assumption that the objects are independent of each other, with no heterogeneity in spatial distribution. That is to say, the spatial correlation has no effect. The assumption obviously goes against the reality. What is worse, the traditional EKC model uses the ordinary least squares (OLS) method in regression estimation. Thus, the spatial autocorrelation test on model residuals is often ignored,

leading to large deviations in the estimation results of the model. To overcome the above defects, the spatial effect should be included in the traditional EKC model, creating an EKC spatial econometric model.

Currently, there are two main types of spatial econometric models: spatial autoregressive (SAR) model and spatial error model (SEM). The SAR model can be expressed as [20]:

$$\begin{cases} y = \rho W_1 y + X \beta + u \\ u = \lambda W_2 + \varepsilon \\ \varepsilon \sim N(0, \sigma_\varepsilon^2 I_n) \end{cases} \quad (6)$$

where, y is the explained variable; X is the set of explanatory variables; ρ and λ are parameters of spatial weight matrix, reflecting the spatial autoregressive property of the model space; W is an $n \times n$ spatial weight matrix of zeros and ones; $W y$ is the product of spatial weight matrix and explained variable, i.e. the degree of influence of spatial correlation on model; ε is a random error.

The SEM can be expressed as [21]:

$$\begin{cases} y = X \beta + \varepsilon \\ u = \lambda W_1 \varepsilon + \mu \\ \varepsilon \sim N(0, \sigma_\varepsilon^2 I_n) \end{cases} \quad (7)$$

where, λ is the spatial error coefficient of an $n \times 1$ -order space, reflecting the degree of spatial autocorrelation for the residual terms of the model; μ is a normally distributed random error; β is the estimation parameter of each explanatory variable, reflecting the degree of influence of each explanatory variable over the explained variable.

Besides economic growth, CO₂ emissions are also influenced by such factors as industry, energy and policy. Hence, four influencing factors were included in the EKC model as control variables:

(1) Industrial structure (IND)

The proportion of different industries in the national economy is closely related to CO₂ emissions. The secondary industry consumes much more energy than primary and tertiary industries. Therefore, the proportion of secondary industry in the national economy is positively correlated with CO₂ emissions.

(2) Energy consumption structure (ECS)

China is a large consumer of coal, a high-carbon energy source. The energy consumption structure can be measured by the proportion of coal in the total amount of energies being consumed. The greater the proportion is, the higher the CO₂ emissions.

(3) Level of opening (OPL)

The growing level of opening, especially the rise of import/export trade, helps the host country to introduce and absorb advanced low-carbon technologies and management skills. In this way, the regional energy consumption will become less intense, which promotes energy-saving and emissions reduction.

(4) Environmental regulation (ERS)

The Chinese government uses environmental regulation as a macro-control tool to protect the environment. In general, the CO₂ emissions of enterprises are controlled by pollution charging system and emissions trading system.

Based on the above control variables and formulas (5)-(7), an EKC spatial econometric model (a general fixed spatial effect model) was established for the relationship between economic growth (per capita GDP) and environmental pollution (per capita CO₂ emissions):

$$\begin{aligned} LnPCO_{2i,t} = & \alpha_i + \phi_t + \beta_1 LnPGDP_{i,t} + \\ & \beta_2 Ln(PGDP_{i,t})^2 + \beta_3 LnIND_{i,t} + \beta_4 LnECS_{i,t} + \\ & \beta_5 LnOPL_{i,t} + \beta_6 LnERS_{i,t} \\ & + \delta \sum_j W_{ij}(PCO_{2i,t}) + \mu_{i,t} \\ \mu_{i,t} = & \lambda \sum_j W_{ij} * \mu_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (8)$$

where, α_i and ϕ_t are fixed spatial effect and fixed time effect, respectively; δ and λ are spatial autoregressive coefficient and spatial error coefficient, respectively. Both δ and λ are related to spatial correlation in the model. If δ is zero and significant, then the model is an SEM; if λ is zero and significant, then the model is an SAR model.

The explained variable of the model is PCO_2 : the ratio of the estimated CO₂ emissions of a province to the year-end resident population of that province.

The main explanatory variables of the model are the first- and second-order terms of per-capita GDP (PGDP). The estimation coefficients of the two terms reflect the form of the EKC.

The control variables of the model include industrial structure (IND) (the proportion of the total output of secondary industry in a province to the GDP of that province), energy consumption structure (ECS) (the proportion of coal consumption to the total energy consumption in each province), level of opening (OPL) (the ratio of the total import/output value, which is converted from USD into RMB at the mean exchange rate, to the GDP in each province), and environmental regulation (ERS) (the ratio of the investment on industrial pollution control to the total industrial output, measured in the unit of 10⁴ yuan, in each province).

2.5 Data sources

Considering data availability and completeness, the panel data in 2000-2017 of 30 Chinese provinces were selected for our research. Tibet, Hong Kong, Macao and Taiwan were

excluded, because the data on these provinces are incomplete. The research data were collected from the *China Statistical Yearbook*, *China Statistical Yearbook on Environment*, *China Energy Statistical Yearbook*, and local statistical yearbooks. The collected data mainly cover the following variables: different types of energies, GDP, per capita GDP, year-end resident population, total output of secondary industry, total import/export value, investment on industrial pollution control, and total industrial output.

3. RESULTS

3.1 Province difference in per capita CO₂ emissions

Based on the data of various energies, the CO₂ emissions of the 30 provinces were estimated by formula (1). Then, the CO₂ emissions of each province were divided by the year-end resident population, yielding the per capita CO₂ emissions of each province. The mean per capita CO₂ emissions of each province in 2000-2017 is displayed in Figure 1.

It can be seen that the provinces differed greatly in per capita CO₂ emissions. The top 5 provinces in per capita CO₂ emissions are Inner Mongolia, Ningxia, Shanxi, Tianjin, and Liaoning. The per capita CO₂ emissions of these provinces were all above 9.5 tons. The high per capita CO₂ emissions can be explained as follows: Located in central and western regions, Inner Mongolia, Ningxia, and Shanxi are major coal producers in China. In recent years, a huge amount of coal has been consumed by the booming industry, emitting a lot of CO₂. Tianjin and Liaoning are coastal provinces in the eastern region. The two provinces have a large demand for fossil energy, because their industrial systems are complete and dominated by heavy industry.

Hunan, Jiangxi, Guangxi, Sichuan, and Hainan were the bottom five provinces in the ranking of per capita CO₂ emissions. The per capita CO₂ emissions of these provinces were below 3.5 tons. The low per capita CO₂ emissions are attributable to the following factors: The five provinces consume relatively little fossil energy, because of their relatively backward economy, late start of industrial system, and low proportion of heavy industry. Located in the southern region, these provinces boast abundant hydropower resources, and their energy structure is mainly supported by hydropower.

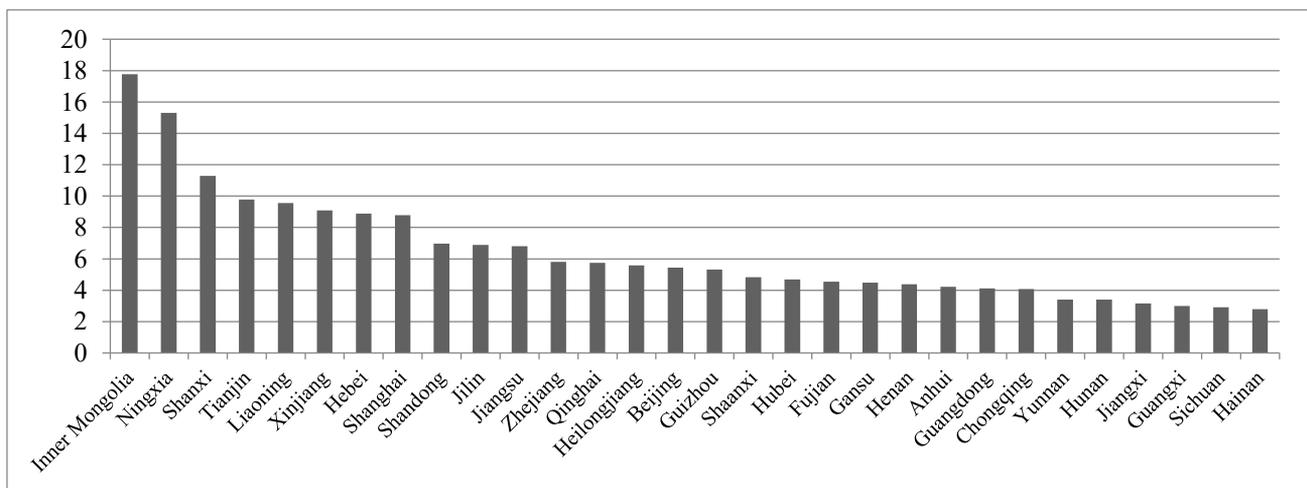


Figure 1. The mean per capita CO₂ emissions of each province in 2000-2017 (unit: ton)

3.2 Spatial effect of per capita CO₂

Based on the spatial weight matrix of zeros and ones, GeoDa software was adopted to compute the Global Moran's I values of the per capita CO₂ emissions of 30 provinces in 2000-2017. The results in Table 1 show that the Global Moran's I values of provincial per capita CO₂ emissions were always positive, passing the significance test on the 5% or 1% level. This means the per capita CO₂ emissions of different provinces have obvious spatial correlation, which greatly

affect the changes in provincial per capita CO₂ emissions. Further, it can be concluded that the provincial per capita CO₂ emissions are distributed as clusters, instead of a random and free form; the per capita CO₂ emissions of neighboring provinces are similar to each other. Therefore, the spatial effect must be included in the traditional EKC model, before probing into the relationship between economic growth and CO₂ emissions. Otherwise, the model estimation will have significant deviations.

Table 1. Global Moran's I values of provincial per capita CO₂ emissions in 2000-2017

Year	Global Moran's I	Error (I)	Standard deviation (I)	Mean	P-value
2000	0.3841	-0.0345	0.1203	-0.0370	3.5004
2001	0.3559	-0.0345	0.1233	-0.0329	3.1533
2002	0.3298	-0.0345	0.1202	-0.0395	3.0724
2003	0.2861	-0.0345	0.1179	-0.0356	2.7286
2004	0.4201	-0.0345	0.1202	-0.0450	3.8694
2005	0.4103	-0.0345	0.1249	-0.0280	3.5092
2006	0.3293	-0.0345	0.1211	-0.0342	3.0017
2007	0.3833	-0.0345	0.1159	-0.0394	3.6471
2008	0.3586	-0.0345	0.1096	-0.0377	3.6159
2009	0.3323	-0.0345	0.1093	-0.0321	3.3339
2010	0.3814	-0.0345	0.1107	-0.0351	3.7624
2011	0.3146	-0.0345	0.1065	-0.0375	3.3061
2012	0.3197	-0.0345	0.1072	-0.0364	3.3218
2013	0.3440	-0.0345	0.1093	-0.0330	3.4492
2014	0.3412	-0.0345	0.1159	-0.0359	3.2537
2015	0.3214	-0.0345	0.1105	-0.0344	3.2199
2016	0.307	-0.0345	0.1137	-0.0316	2.9780
2017	0.2621	-0.0345	0.1072	-0.0427	2.8433

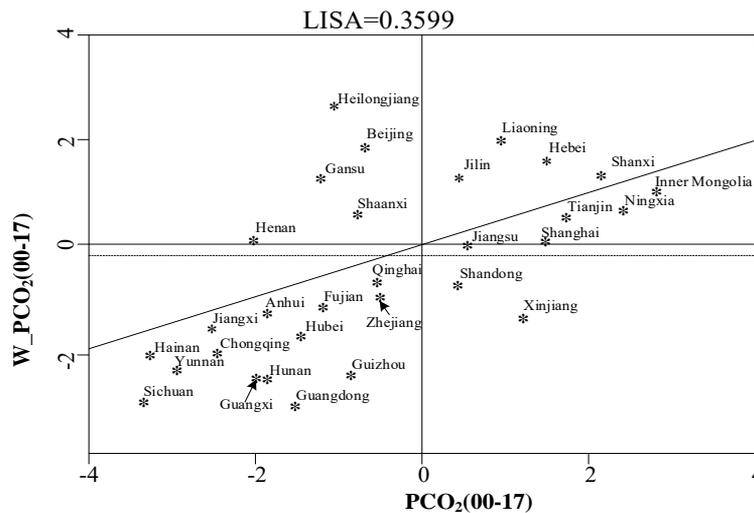


Figure 2. The LISA scatter plot for the mean per capita CO₂ emissions of each province in 2000-2017

The next step is to observe the local distribution of provincial per capita CO₂ emissions in space. The LISA scatter plot (Figure 2) was prepared for the mean per capita CO₂ emissions of each province. There are four quadrants in the scatter plot: the first quadrant is the cluster area of high values (HH); the second quadrant is an area of spatial outliers; the third quadrant is the cluster area of low values (LL); the fourth quadrant is another area of spatial outliers.

In the first quadrant, the per capita CO₂ emissions of a province and its neighbors are both high; in the second quadrant, the per capita CO₂ emissions of a province are high, while those of its neighbors are low; in the third quadrant, the

per capita CO₂ emissions of a province and its neighbors are both low; in the fourth quadrant, the per capita CO₂ emissions of a province are low, while those of its neighbors are high. The provinces falling in the first and third quadrants belong to typical cluster areas, while those falling in the second and fourth quadrants belong to atypical areas of spatial outliers.

As shown in Figure 2, 30% of all provinces fell in the first quadrant, including Inner Mongolia, Ningxia, Tianjin, Shanghai, Jiangsu, Shanxi, Hebei, Liaoning and Jilin; these provinces belong to the typical cluster area of high values. 16.67% of all provinces fell in the second quadrant, including Heilongjiang, Gansu, Beijing, Shaanxi and Henan; these

provinces belong to an atypical area of spatial outliers. 46.66% of all provinces fell in the third quadrant, including Qinghai, Zhejiang, Anhui, Chongqing, Fujian, Hubei, Guizhou, Jiangxi, Yunnan, Hunan, Guangdong, Hainan, Sichuan, and Guangxi; these provinces belong to the typical cluster area of low values. 6.67% of all provinces fell in the fourth quadrant, including Shandong and Xinjiang; the two provinces belong to another atypical area of spatial outliers.

To sum up, the per capita CO₂ emissions of most (76.66%) provinces fell in the first and third quadrants, i.e. typical cluster areas, while only 23.34% provinces fell in the second and fourth quadrants. The results afford evidence as to the local spatial heterogeneity of provincial per capita CO₂ emissions in China.

3.3 Empirical results of EKC spatial econometric model

This paper first performs regression analysis on model (8) by the OLS, and then uses Matlab 7.12 to test the significance of the spatial autocorrelation of the residual terms of the model. The estimated results are listed in Table 2.

To prove the necessity of controlling the fixed effects, Table 2 also provides the estimated results of the non-fixed effect models, the spatial fixed effects model, the time fixed effects model and the two-way fixed effects model. The results of the four models were compared to reveal the importance of controlling the fixed effects to model accuracy.

Table 2. Estimated and test results of general panel data models

Variables	Non-fixed effects model	Spatial fixed effects model	Time fixed effects model	Two-way fixed effects model
<i>LnPGDP</i>	-0.1803 (-0.4695)	1.2823*** (6.8059)	0.2101 (0.5328)	0.8187*** (4.3577)
<i>Ln(PGDP²)</i>	0.0420** (2.1721)	-0.0365*** (-3.8182)	0.0371** (1.9031)	-0.0196** (-1.9543)
<i>LnIND</i>	0.2155*** (2.7100)	0.3726*** (6.7890)	0.1314* (1.7217)	0.4572*** (6.5452)
<i>LnECS</i>	0.6623*** (14.5124)	0.3781*** (13.02886)	0.6172*** (14.6187)	0.4001*** (14.5715)
<i>LnOPL</i>	-0.0165 (-1.0036)	-0.0102 (-0.5242)	-0.1271*** (-5.3647)	-0.0147 (-0.7358)
<i>LnERS</i>	0.2008*** (11.5285)	0.0518*** (6.4450)	0.2728*** (14.0328)	0.0696*** (6.7079)
<i>R-squared</i>	0.7642	0.9181	0.6985	0.9614
<i>Log-L</i>	121.8205	398.1032	73.1410	437.2438
<i>DW</i>	1.0181	2.0464	1.4857	2.3901
<i>LM-lag</i>	74.1350***	14.1730***	62.7034***	0.2481
Robust <i>LM-lag</i>	1.7872	11.2657***	25.9982***	5.5222**
<i>LM-err</i>	158.2981***	4.7148**	38.2598***	5.4157**
Robust <i>LM-err</i>	85.9503***	1.8075	1.5545	10.6898***

Note: The bracketed data are t-test results; *, **, and *** are significance levels of 10%, 5% and 1%; model estimation and spatial autocorrelation test were conducted on Matlab 7.12.

Table 3. Estimated and test results of spatial econometric models with two-way fixed effects

Variables	SAR	SEM
<i>LnPGDP</i>	0.8621*** (4.4232)	0.9528*** (5.5463)
<i>Ln(PGDP²)</i>	-0.0217** (-2.1132)	-0.0282*** (-3.0526)
<i>LnIND</i>	0.4513*** (6.4189)	0.4721*** (6.7460)
<i>LnECS</i>	0.4020*** (14.6359)	0.4032*** (15.2782)
<i>LnOPL</i>	-0.0155 (-0.7773)	-0.0384** (-1.9955)
<i>LnERS</i>	0.0694*** (6.7283)	0.0667*** (6.5721)
<i>W*dep.var.</i>	-0.0299 (-0.6442)	
<i>spat.aut.</i>		-0.2100*** (-3.4133)
<i>R-squared</i>	0.9703	0.9702
<i>Log-L</i>	437.3773	441.4579

Note: The bracketed data are t-test results; *, **, and *** are significance levels of 10%, 5% and 1%.

As shown in Table 2, the coefficients of determination, i.e. R-squared, of the non-fixed effect models, the spatial fixed effects model, the time fixed effects model and the two-way fixed effects model were 0.7642, 0.9181, 0.6985 and 0.9614, respectively. The two-way fixed effects model had the largest

coefficient of determination, and thus the best goodness of fit. The two-way fixed effects model also achieved the largest value, in terms of log-likelihood (Log-L) and Durbin -Watson (D-W) statistic. The above results show that the two-way fixed effects model has better estimation results than the other three

models. Therefore, this model was adopted to interpret the relationship between variables.

The lower half of Table 2 presents the test results on the spatial autocorrelation of the residual terms of the model. The lag of the Lagrange Multiplier (LM) test, denoted as LM-lag, was 0.2481, failing to pass the significance test; the LM-error, denoted as LM-err, was 5.4157, which passed the significance test on the level of 5%. The results show that the residual terms have obvious spatial autocorrelation. If not resolved, the spatial autocorrelation will lead to bias in model estimation.

The spatial autocorrelation of the residual terms cannot be eliminated by general models. Hence, spatial econometric models with two-way fixed effects were adopted to re-simulate model (8). The estimated results of the SAR model and the SEM are compared in Table 3.

As shown in Table 3, the SAR model's spatial lag, $W^*dep.var.$, was -0.0299, failing to pass the significance test. Thus, the SAR model is not suitable for this research. By contrast, the SEM had a spatial error, $W^*dep.var.$, of -0.2100, which passed the the significance test on the level of 1%. The comparison proves that the SEM is the best form of our spatial econometric model.

Compared with general models, the SEM output very large R-squared and Log-L, the same sign of the estimation coefficient of each variable, and a large t-statistic. This means the spatial econometric model optimized the results of general models. Therefore, the SEM was selected to interpret the estimation coefficient of each variable.

As shown in Table 3, the estimation coefficient of $LnPGDP$ and that of $Ln(PGDP^2)$ of the SEM were positive and negative, respectively. Thus, there must be one inflection point of the EKC spatial model, which is in line with the basic form of the traditional EKC: economic growth has an inverted U relationship with CO₂ emissions. The relationship is divided by the inflection point into two stages (Figure 3).

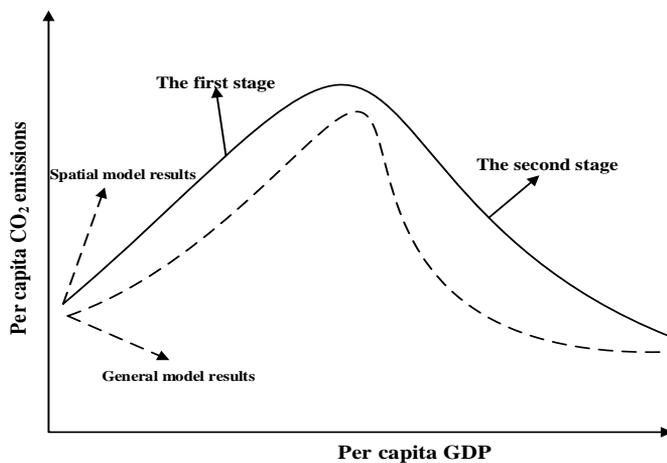


Figure 3. The inverted U relationship between per capita GDP and per capita CO₂ emissions

In the first stage, the estimation coefficient of $LnPGDP$ was 0.9528 and significant on the 1% level. This means the rapid economic growth brings lots of CO₂ emissions, when the economy just starts to develop. In general, economic growth is reflected in three dimensions: scale, structure and technology. When the economy just starts to develop, the government emphasizes the expansion of economic scale over the structural upgrading and the technical progress. That is why China's economic growth is featured by high investment,

pollution and emissions. Under this extensive growth mode, the fast growing economy must be backed up by lots of production factors. The consumption of fossil energy takes up a large portion of production factors, which obviously increase the intensity of CO₂ emissions.

In the second stage, the estimation coefficient of $Ln(PGDP^2)$ was -0.0282 and also significant on the 1% level. This means, with the continuous growth of per capita GDP, further economic growth suppresses CO₂ emissions. It can be seen that, once economy surpasses a threshold, the environmental awareness will grow with the rising income, i.e. people will raise higher demand for high-quality eco-environment. Meanwhile, the government will gradually recognize the importance of low-carbon transformation of economic development, and promote the shift from scale to quality. At this time, the government will vigorously implement industrial upgrading and transformation, eliminate backward industries and reduce excess capacity. In addition, the government will encourage enterprises to adopt new low-carbon technologies and upgrade production equipment, thereby reducing the intensity of energy consumption and controlling emissions. Overall, CO₂ emissions are cut down by structural optimization and advanced technologies, indicating that economic growth in the second stage helps to reduce CO₂ emissions.

Judging by the estimated results, the control variables have different degrees of impact on CO₂ emissions.

The industrial structure (IND) had a positive impact on per capita CO₂ emissions on the significance level of 1%, indicating that the proportion of the output of secondary industry in GDP promotes the per capita CO₂ emissions. The result indicates that China is still in the stage of rapid industrialization, and industry takes and will take a large portion in national economy. This also means that fossil energy consumption remains high.

The energy consumption structure (ECS) had a positive impact on per capita CO₂ emissions on the significance level of 1%, indicating that the proportion of coal in the energy structure promotes the per capita CO₂ emissions. This finding echoes with the relevant data: In 2017, coal took up 62% of all energies being consumed, while clean energies like nuclear power and hydropower occupied less than 20%. As a traditional coal consumer, China still has a coal-dominated energy structure, which clearly promotes CO₂ emissions.

The level of opening (OPL) had a negative impact on per capita CO₂ emissions on the significance level of 5%, indicating that import/export trade suppresses the per capita CO₂ emissions. The result validates the previous assumption that: As China deepens foreign trade, the trade products will gradually shift from low-end products to high-tech products. The gradual shift promotes the low-carbon upgrading of regional industry, and lowers the intensity of energy consumption.

The environmental regulation (ERS) had a positive impact on per capita CO₂ emissions on the significance level of 1%, indicating that the rise in the investment on industrial pollution control actually promotes CO₂ emissions. A possible reason is the immature system of environmental regulation in China. The excessive government intervention has not forced enterprises to reduce emissions, but distorted the resource allocation, creating the environmental paradox.

Figure 3 also compares the estimated results of general model and our spatial model. It can be seen that the estimated results of both models exhibited as inverted U curves.

However, the inverted U curve of our spatial model was higher and steeper than that of the general model. Therefore, the economic growth in our spatial model has greater impact on CO₂ emissions than that in the general model. Moreover, the inflection point of our spatial model appeared earlier than that of the general model. Thus, the general model has a certain lag in EKC estimation, inducing errors in environmental policies.

4. DISCUSSION

Over the past 40 years, China has developed into the second largest economy in the world, with an annual economic growth rate of 9.5%. The economic growth is accompanied by heavy energy consumption and severe eco-environmental problems. Being the largest CO₂ emitter, China must take more energy-saving and emissions reduction measures to achieve the goal of reducing the CO₂ emission per unit of GDP by 40-45% before 2020. Unfortunately, neither the intensity of energy consumption nor that of CO₂ emissions is expected to decline, for the country is striving to build a well-off society in an all-round and further promoting industrialization and urbanization.

Against this backdrop, the Chinese government is faced with an arduous task: Under the premise of maintaining the healthy economic growth, controlling CO₂ emissions within a reasonable range, without severely affecting energy supply and daily lives. To effectively promote energy-saving and emissions reduction, it is critical to explore the internal relationship between economic growth and CO₂ emissions, and identify the influencing factors of CO₂ emissions.

The traditional EKC model ignores the spatial dependence in the relationship between economic growth and CO₂ emissions, which leads to errors in research conclusions. Referring to theories of spatial econometrics, this paper introduces the spatial effect into the traditional EKC model, and takes industrial structure, energy consumption structure, level of opening and environmental regulation as control variables. On this basis, an EKC spatial econometric model was established with multiple control variables, and used to verify if the relationship between economic growth and CO₂ emissions in China satisfies the EKC model.

From a fresh perspective, this research validates the assumption that the relationship between economic growth and CO₂ emissions can be illustrated as an EKC, estimates the EKC of the CO₂ emissions in China in an accurate manner, and correctly predicts the form and inflection point of the curve. In addition, the influencing factors (other than economic growth) of CO₂ emissions and their degree of impacts were analyzed accurately, enabling governments at all levels to formulate reasonable carbon reduction policies.

5. CONCLUSIONS

Energy depletion and environmental pollution are two major bottlenecks of sustainable development of economy in China. Thus, it is of great significance to coordinate the development of economy, energy and environment. This paper selects the panel data in 2000-2017 of 30 provinces as objects, estimates the CO₂ emissions of each province, and calculates provincial per capita CO₂ emissions. Next, the spatial autocorrelation coefficient and the LISA scatter plot were adopted to study the spatial effect of per capita CO₂ emissions. Finally, the spatial effect was introduced to the traditional

EKC model, creating an EKC spatial econometric model about the relationship between economic growth and CO₂ emissions. The research results are as follows:

First, the provinces differed greatly in per capita CO₂ emissions. Based on the mean value in 2000-2017, the per capita CO₂ emissions of Inner Mongolia, Ningxia, Shanxi, Tianjin, and Liaoning were all above 9.5 tons, while those of Hunan, Jiangxi, Guangxi, Sichuan and Hainan were all below 3.5 tons.

Second, the Global Moran's I values show a significant spatial correlation between provincial per capita CO₂ emissions. The LISA scatter plot indicates that, in terms of per capita CO₂ emissions, most provinces belong to the cluster areas of high values (H-H) and low values (L-L), while only a few belong to the areas of spatial outliers. The results indicate the local spatial heterogeneity of provincial per capita CO₂ emissions.

Third, the EKC spatial econometric model outperforms the general econometric model in estimation accuracy. Besides, the EKC spatial econometric model shows that the economic growth has a significant inverted U relationship with CO₂ emissions. In other words, with the growth in economy, the CO₂ emissions firstly increase and then decrease. The two-stage relationship obeys the basic form of the traditional EKC.

Fourth, the estimated results of control variables indicate that CO₂ emissions are clearly promoted by industrial structure, energy consumption structure and environmental regulation, but suppressed by the level of opening.

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