Short Research Article

Environmental Kuznets Curve of HouseholdElectricity Consumption in China: Based on Spatial Econometric Model

Abstract: In this paper,the spatial measurement model is introduced into the Environmental Kuznets Curve to investigate the impact of income on household electric carbon emissions. The spatial correlation diagnosis was made by using Moran scatterplot and Moran index. The results of spatial error model show that the Environmental Kuznets Curve of householdelectric carbon emissions is inverted N-shaped carve. The maximum and minimum values of Environmental Kuznets Curve are per capita GDP of RMB 10198 Yuan and RMB 44355 Yuan (at constant price in 2005). It means that the per capita household electricity carbon emissionsare still on the rise in most provinces of China.

Keywords: household electricity carbon emission; environmental Kuznets curve; spatial measurement model

1Introduction

The entry into force of the Kyoto protocol in 2005, the Copenhagen climate conference in 2009 and the formulation of the Paris agreement in 2016 revealed that all countries in the world have paid great attention to the issue of climate change. At present, greenhouse gases, such as carbon dioxide, is a key factor leading to climate change. Energy conservation and emission reduction is an urgent need to cope with global climate change and an inevitable choice to build a resource-conserving and environment-friendly society.

Along with the economic growth and the improvement of residents' living standards, the householdelectricity consumption continues to grow rapidly, accounting for an increasing proportion of the electricity consumption of the whole society. According to the data of electricity consumption released by the National Energy Administration of China in 2016, electricity consumption reached 5919.8 billion kWh, up by 5.0% year on year; Urban and rural residents consumed electricity of 805.4 billion kWh, up 10.8% year on year.The proportion of household electricity consumption on the total electricity consumption is only slightly more than 13%, while that of developed countries is about 20%. At the same time, through the horizontal comparison of the data of per capita household electricity consumption in various countries in 2015, the per capita household electricity consumption in most developed countries is1000~4000 kWh, and the per capita household electricity consumption in the United States and Canada has reached 4486 kWh and 4617 kWh respectively. However, China's per capita household electricity consumption is 529 kWh, which is about 1/9 that of the United States and Canada and far lower than the level of developed countries. Through the lateral comparison of the data of per capita household electricity consumption in various provinces of China in 2015,Fujian ranked first with per capita household electricity consumptionof 898.57 kWh; per capita household electricity consumption of other developed provinces and cities is more than 700 kWh, such as Beijing, Shanghai, Zhejiang and Guangdong; that is relatively low in most of the less developed provinces (such as Xinjiang, Qinghai, Ningxia and Gansu), which is under 400 kWh; that is 400~700 kWh basically in other provinces. That means there is still huge room for growth. So household electricity carbon emissions cannot be ignored in order to reduce carbon emissions.

Income is one of the main driving factor of household electricity consumption, and the difference in household electricity consumption between different regions can be explained by the income gap between China and developed countries or among 30 provinces. Countries or regions with higher economic development tend to have higher per capita household electricity consumption. For developed economies, the per capita energy consumption basically shows an inverted u-shaped pattern(Zheng, 2016). So given the trend of increasing income, will per capita household electricity carbon emissions continue to grow in China or will they start to decline when the income reaches a certain level? If there is a turning point, where is the turning point? In order to answer these questions, the current general method is the empirical research of the Environmental Kuznets Curve (EKC) to judge whether and when the pollution peak exists.

2Literature review

EKC theory originated from the study on the relationship between atmospheric environment and per capita income in North American Free Trade Agreement(NAFTA) (Grossman and Krueger, 1991). This study found that there was a significant inverted U-shaped curve relationship between smog, suspended matter and per capita income. Later, Panayotou (1993) studied the relationship between different environmental pollutants and income levels based on Grossman and Krueger's study, and found that there was also an inverted U-shaped curve relationship between the two, which was called the Environmental Kuznets Curve (EKC). EKC theory is an empirical hypothesis, and the related researches mainly focus on the empirical aspects. EKC theory assumes that environmental quality will deteriorate with income growth, but environmental quality will improve with income growth when income reaches a certain level. In essence, the EKC theory reflects the process of transforming the economic development model with high energy consumption and high pollution into a resource-conserving and environment-friendly one, indicating that the economic growth target is beneficial in the long run.

In the context of global warming, more and more Chinese scholars have combined carbon emission and EKC theory to discuss. Some studies analyzed the total national carbon emissions, such as Hu et al. (2008). Based on EKC theory, they built the factor decomposition model of carbon emissions in China to analyze the impact of economic scale and other factors on carbon emissions, and found that there was an inverted N-shaped curve relationship between carbon emissions and economic growth. There are also some studies that analyze the carbon emissions of a certain industry or department in a certain region. For example, Yan et al. (2018) found an inverted N-shaped curve relationship between the carbon emissions of the construction industry in Guangdong province and the per capita output value of the construction industry based on the EKC. Tian and Xie (2017) found that China's agricultural per capita carbon dioxide emissions and per capita GNP showed an inverted U-shaped curve relationship based on the research of EKC theory, and China's agricultural carbon emissions were at the left of the inflection point of the inverted U-shaped curve. Current form of EKC not only limited to the inverted U-shaped curvebecause the Non-income factors can also affect the form. The third power of item of the per capita GDP is used when verifying the existence of EKC. Because the measure of the inflection points of the corresponding high per capita income levels when only contains second power of per capita GDP (Xu and Song, 2010).And the non-income factors should be consideredtoo.

In recent years, there are more and more researches on the combination of EKC and spatial econometric model. Yang et al. (2008) studied the relationship between air quality and economic growth of 46 cities in China by combining EKC and spatial econometric model. Wu and Tian (2012) analyzed the spatial correlation, EKC shape and determinants of provincial environmental pollution based on the EKC theory and spatial econometric model. Hao et al. (2014)found that there is strong spatial correlation between China's economic growth and energy or electricity consumption per capita, and the energy or power consumption per capita and Per capita GDPhave the N-shaped EKC relationship by choosing the appropriate spatial econometrics model to the Chinese provincial per capita energy consumption and power consumption per capita for empirical research.

When investigating the relationship between household electricity carbon emission and income, it is unreasonable to use EKC equation directly, because the hypothesis of spatial data independence of EKC is obviously inconsistent with reality.First of all, China's regional economic development is unbalanced. Each region has its own characteristics and forms its own "convergence club". Second, the economic behavior of the current decision of regional economies is often affected by the previous or current behavior of other economies (Le Sage and Pace, 2009), for example local government perhaps referencethe policies of electricity price and energy conservation of the neighborhoods and then make therelevant policies.And city is a nodes of social economic and social resources in the economic region and the residents' consumption behavior is related to economic and social development level (Mi, 2011). Moreover, there are differences in the endowment of power resources between different provinces in China, and there are contradictions between the endowment of power resources and demand, which leads to a large number of power transmission and allocation among regional power grids in China. However, the carbon emission coefficient of power in different regions is obviously different. So it is unreasonable to investigate the influence of local electricity carbon emissions on local regions only from the perspective of consumption (Fu and Qi, 2014). Finally, temperature will also affect the electricity consumption of residents. Chen et al. (2017) found that the colder the household area is, the less willing residents are to save energy, and the temperature of adjacent areas is often similar. Therefore, it may be biased to ignore the spatial characteristics when examining the household electricity carbon emissions. Spatial econometrics abandons the traditional assumption that econometrics has no spatial relevance, and introduces a spatial weight matrix to consider the impact of spatial correlation on economic activities, so as to eliminate the spatial bias in the calculation results.

Income is one of the key factors that affect the consumption of electricity, and the price of electricity will also affect the consumption of electricity. However, in China, the household electricity price has been cross-subsidized for a long time, which is lower than the industrial electricity price. The household electricity price has not changed much in the past dozen years (Lin and Liu, 2016), so this paper does not consider the household electricity price.

Factors such as population density and urbanization rate will also affect the household electricity consumption. Jones and Kammen (2014) pointed out that there was a negative correlation between population density and carbon emissions, which means carbon emissions would decrease with the increase of population density. However, their study of the spatial distribution of household carbon footprint in the United States showed that the result was consistent with previous studies considering only urban data. However there appeared to be a small positive correlation between household carbon emissions and population density when considering the whole region or country. At the same time, it is found that population density may affect the intensity of household carbon emission by influencing the size of houses.Ding (2011) and Wang et al. (2012) decomposed the carbon dioxide emissions of household energy consumption and found that the population scale effect, income level, urban-rural structure and other factors are the key factors affecting the carbon emissions of household energy consumption.

Therefore, this chapter will introduce urbanization rate and population density to expansion EKC theory and select the space panel econometric model to study the household electricity carbon emissions in China. The main innovation of this paper is to investigate the spatial correlation of household electric carbon emissions. The rest of this paper is structured as follows: the third part briefly introduces the model, estimation method and data to be used in this paper; the fourth part carries on the spatial autocorrelation test, and uses the spatial econometric model to carry on the demonstration analysis; the fifth part is the conclusion.

3Econometric model

3.1Basic econometric model

3.1.1Model reference form

This paper introduces the EKC equation containing the third power terms of per capita GDP as the basic form of the regression equation, and introduces the controlling variables, urbanization rate and population density, to expand the EKC equation:

$$\mathrm{lnE}_{i,t} = \alpha_i + \beta_1 \mathrm{lny}_{i,t} + \beta_2 (\mathrm{lny}_{i,t})^2 + \beta_3 (\mathrm{lny}_{i,t})^3 + \beta_4 \mathrm{lnUR}_{i,t} + \beta_5 \mathrm{lnPD}_{i,t} + \varphi_{i,t} \quad (1)$$

$E_{i,t}$represents carbon emission generated by per capita household electricity consumption of the province *i* in the year *t*, $y_{i,t}$represents per capita GDP of the province *i* in the year t,Although per capita disposable income is often used to investigate the impact on household electricity consumption, per capita GDP is also used in some studies (Sun and Yu, 2017). $UR_{i,t}$ and $PD_{i,t}$represent two control variables: urbanization rate and population density. $\alpha_i$is a random perturbation term, and $\varphi_{i,t}$is a random perturbation term. Different values of β_1, β_2 and $\beta_3$will lead to different shapes of curves, which can be divided into the following 7 cases:

(1) When $\beta_1=\beta_2=\beta_3=0$, there is no relationship between per capita household electricitycarbon emissions and per capita GDP;

(2) When $\beta_1<0$ and$\beta_2=\beta_3=0$, per capita household electricity carbon emissions decrease with the increase of per capita GDP;

(3) When $\beta_1>0$and $\beta_2=\beta_3=0$,per capita household electricity carbon emissions increase with the increase of per

capita GDP;

(4) When β_1<0, β_2>0 and β_3=0, there is a U-shaped relationship between per capita household electricity carbon emissions and per capita GDP;

(5) When β_1>0, β_2<0 andβ_3=0, there is an inverted U-shaped relationship between per capita household electricity carbon emissions and per capita GDP. When carbon emissions start to decline ,the turning point is $y_t = e^{\frac{\beta_1}{2\beta_2}}$;

(6) When β_1<0, β_2>0 andβ_3<0, there is an inverted N-shaped relationship between per capita household electricity carbon emissions and per capita GDP, which means that per capita household electricity carbon emissions start to increaseat the first turning point, and decrease with the growth of per capita GDP at the second turning point.

(7) When β_1>0, β_2<0 andβ_3>0, there is a N-shaped relationship between per capita household electricity carbon emissions and per capita GDP, which means that the per capita household electricity carbon emissions start to decrease at the first turning point, and increase with the growth of per capita GDP atthe second turning point.

3.1.2 Spatial econometric model

Before introducing spatial autocorrelation factors, spatial correlation test of data should be carried out first. The spatial correlation index is Moran index (Moran, 1950), and its calculation formula is:

$$\mathrm{I} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}W_{i,j}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{i,j}\sum_{i=1}^{n}(x_i-\bar{x})^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{i,j}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}W_{i,j}} \quad (2)$$

Where, Iis the Moran index, $x_i$is the observed value of the explained variable in the region *i*, *n* is the total number of regions, $W_{i,j}$is the spatial weight matrix.Different forms of space weight matrix will not substantially change the result of space regression (Wu and Tian, 2012).Therefore, this paper adopts the adjacent weight matrix. if space region I is adjacent to j, then $W_{i,j}$=1; otherwise,$W_{i,j}$=0. The value range of Moran index is [-1, 1]. When Moran index is greater than 0, it means there is positive spatial autocorrelation; when it is less than 0, it means there is negative spatial correlation.

When Moran index indicates the spatial dependence of panel data, the spatial panel model can be introduced, which may contain the dependent variable of spatial lag or the error term of spatial autoregressive. Elhorst (2012) proposed three basic spatial econometric models, namely spatial lag model (SLM), spatial error model (SEM) and spatial Durbin model (SDM).

The basic form of SLM is:

$$\mathrm{Y}_{i,t} = \rho\sum_{i=1}^{N}W_{i,j}Y_{j,t} + \alpha + \beta X_{i,t} + \mu_i + \eta_t + \varphi_{i,t} \quad (3)$$

Where, *i*=1, ..., N, and *t*=1, ..., T. $Y_{i,t}$represents the cross-sectional observation value of unit *i*at time *t*, which is an N×1dimensional vector composed of explained variables. $X_{i,t}$ is the explanatory variable. P represents the spatial regression coefficient, $W_{i,j}$represents the space weight matrix, the paper uses the adjacent weight matrix, namely, such as space region I and j adjacent, then $W_{i,j}$=1, otherwise $W_{i,j}$=0. α denotes the constant term, βdenotes the estimated coefficient of the explanatory variable; $\mu_i$stands for space effect; $\eta_t$means time fixed effect; $\varphi_{i,t}$means independent homodistributed error term.

The basic form of SEM is:

$$Y_{i,t} = \beta X_{i,t} + \mu_i + \eta_t + \varphi_{i,t} \quad (4)$$

$$\varphi_{i,t} = \lambda \sum_{j=1}^{N} W_{i,j}\varphi_{j,t} + \varepsilon_{i,t} \quad (5)$$

Where, $\varphi_{i,t}$ is the spatial autocorrelation error term, λ is the spatial error coefficient.

The basic form of SDM is:

$$Y_{i,t} = \rho \sum_{j=1}^{N} W_{i,j}Y_{j,t} + \beta X_{i,t} + \lambda \sum_{j=1}^{N} W_{i,j}X_{j,t} + \mu_i + \eta_t + \varphi_{i,t} \quad (6)$$

3.1.3 Correlation testing and estimation methods

This article is based on the steps adopted by Elhorst (2012). Firstly, estimate the spatial panel data model.The estimation methods respectively are mixed OLS, space-fixed effect, time-fixed effect and time-fixed and space-fixed effect. The likelihood ratio test is applied to the fixed effects, and whether the spatial panel data overlooked the space effect of panel data is tested according to each kind of model of LM statistics, which is used to determine what kind of spatial econometrics model.

Secondly, Wald test and LR test are used to test whether SDM can be simplified into SLM or SEM. If both null hypotheses are rejected, the SDM provides the best fit. Finally, Hausman test is used to select random effects and fixed effects.

3.2Data description

This paper mainly adopts two kinds of index data. One is the per capita GDP used to reflect the level of regional economic development, which is expressed by $y_{i,t}$. The other is the carbon emissions caused by the per capita household electricity consumption of provincial residents over the years, which is used to reflect the living electricity consumption of residents, represented by $E_{i,t}$. In the study, the per capita value of household electricity carbon emissions can eliminate the scale effect. Referring to other EKC empirical studies, this paper selected population density and urbanization rate as control variables. The electricity consumption data used in this study were derived from China Energy Statistics Yearbook from 2005 to 2015, and the data of 30 provinces, municipalities and autonomous regions (except Tibet, Hong Kong, Macao and Taiwan) were selected.

According to table 1, the per capita household electricity carbon emissions of residents in each province are calculated as follows:

$$E_{i,t} = CE_{i,t} * F_{i,k} / n_{i,t} \quad (7)$$

Where, $E_{i,t}$ represents the per capita household electricity carbon emissions of residents in the province*i*in the year *t*(*i* =1,2... , 30; *t* = 1, 2,... , 11), and the unit is kg/ person; $CE_{i,t}$ represents the household electricity consumption in the province *i*in the year *t*, and the unit is kWh; $F_{i.k}$ represents the grid emission factor of the region of province*i*, and the unit is kgCO2/kWh; $n_{i,t}$ refers to the resident population of the province*i* in the year t. Table 2 shows the descriptive statistical results of each variable.

Table 1 carbon emission factors of regional power grid in 2015

region	Grid carbon emission factor (unit: $kgCO_2/kWh$)
North China	1.0416
Northeast China	1.1291
East China	0.8112
central China	0.9515
Northwest China	0.9457
South China	0.8959

Note: the carbon emission factor of China's regional power grid in 2015 is the weighted average of the marginal power emission factor from 2011 to 2013.

Table 2 descriptive statistical results of variables

Variable name	unit	mean	standard deviation	maximum	median	minimum
Per Capita Household Electricity Carbon Emissions	kg/person	357.75	153.11	838.65	339.35	118.90
Per Capita Real GDP	Yuan(in the constant of 2005)	28735.49	17674.55	95560.13	24012.71	5376.46
Urbanization Rate	%	51.74	14.13	89.60	49.22	26.87
Population Density	persons/square kilometer	436.96	632.75	3772.94	279.39	7.54

4Empirical results and analysis

4.1Per capita household electricitycarbon emissions distribution and spatial autocorrelation analysis

The software STATA was used to draw the distribution map and Moran scatter plot of the per capita household electricity carbon emissions of Chinese residents in 2005, 2010 and 2015 (seen in figure 1, figure 2 and figure 3). When drawing the carbon emissions distribution map, the same segmentation method is used: 0~300, 300~400, 400~500 and above, and the unit is kg/person. Though the distribution maps of three years, it can be found that the level of per capita household electricity carbon emissions is similar in the adjacent areas. At the same time, per capita household electricity carbon emissions are gradually increased, and that of the coastal areas grow faster. The provinces of 500kg/person carbon emissions are mainly concentrated in coastal areas. It can be concluded from the Moran scatter diagrams that the global Moran's I of per capita household electricity carbon emissions is greater than zero, and the significance test of 1% indicates that per capita household electricity carbon emissions have a significant spatial positive correlation (distribution of agglomeration state), which proves that spatial econometric regression test can be conducted. In 2005, 2010 and 2015, the global Moran's I was 0.321, 0.412 and 0.360 respectively. It can be seen that per capita household electricity carbon emissions have spatial correlation. Moran scatter plot is divided into four quadrants, which embodies the local space contact form. The first, two, three and four quadrant show respectively high-high concentration, low-high concentration and low-low concentration and high-low agglomeration. For example,high-high concentration shows thatif an area is ofhighper capita household electricity carbon emissions, the other areas around the area is of high per capita household electricity carbon emissions.Other types are in the same way. The Moran scatter plots of 2005, 2010 and 2015 at the top left of the pictures shows that 24/30, 26/30 and 22/30 provinces are in the first and third quadrants.That means most provinces or cities are located in the high-high concentration and low-low concentration, which also indicates that per capita household electricity carbon emissions have obvious spatial autocorrelation characteristics. In 2010 and 2015, more provinces were located in high-high concentration than in 2005.

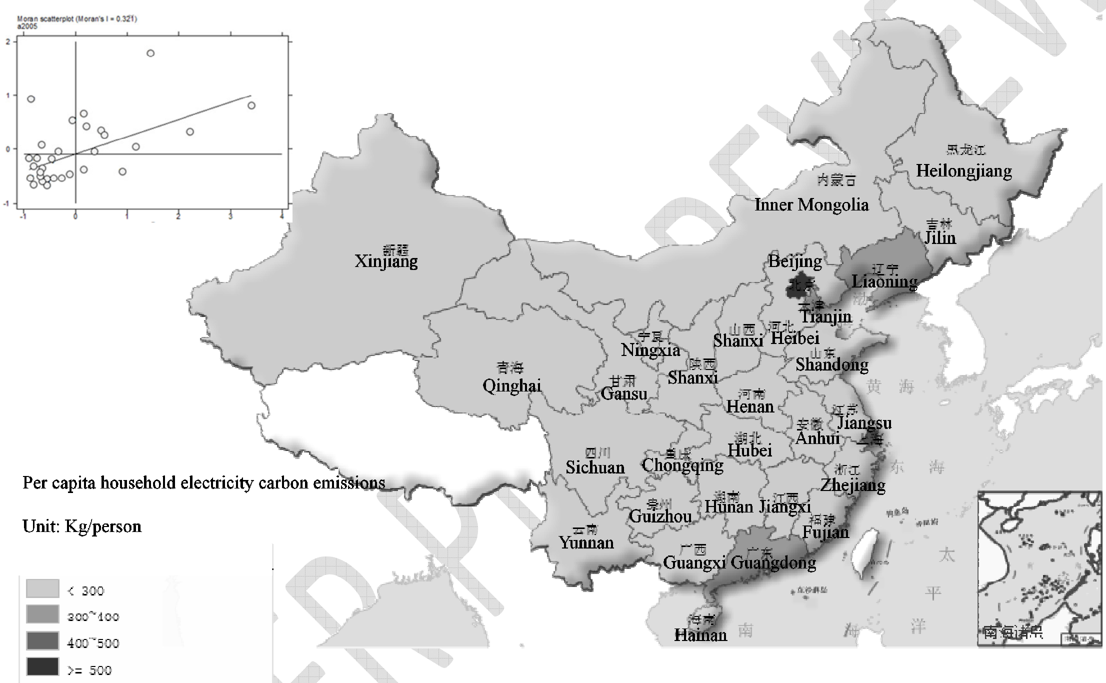

Fig.1 the distribution map and Moran scatter plot of per capita household electricity carbon emissions of Chinese residents in 30 province in 2005

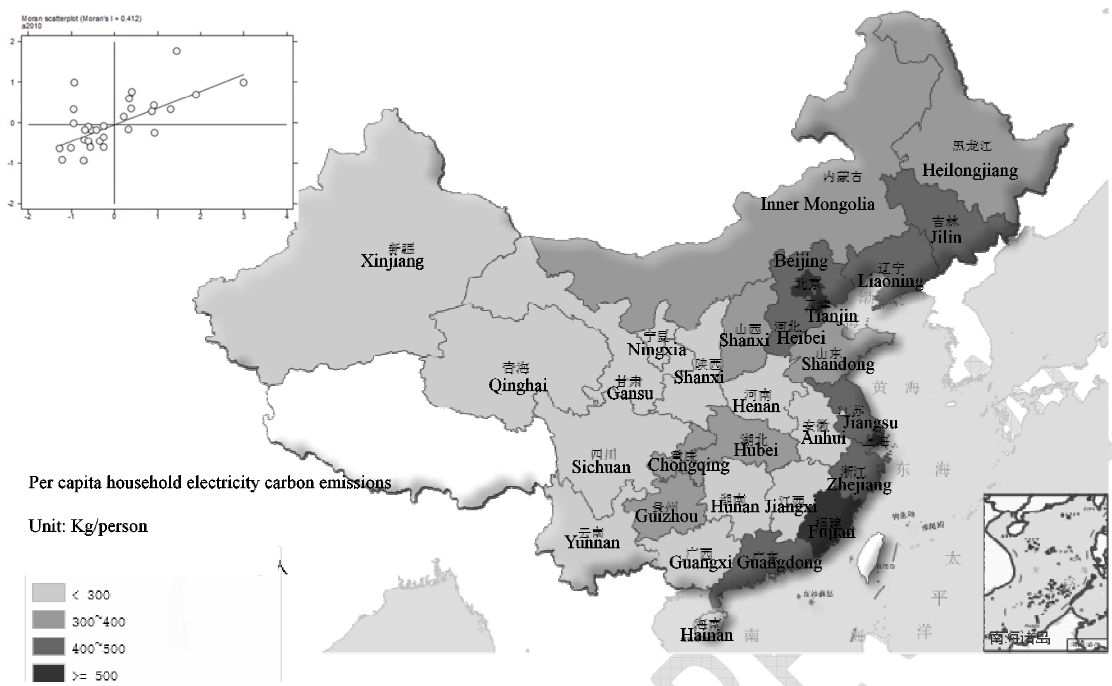

Fig.2 the distribution map and Moran scatter plot of per capita household electricity carbon emissions of Chinese residents in 30 province in 2010

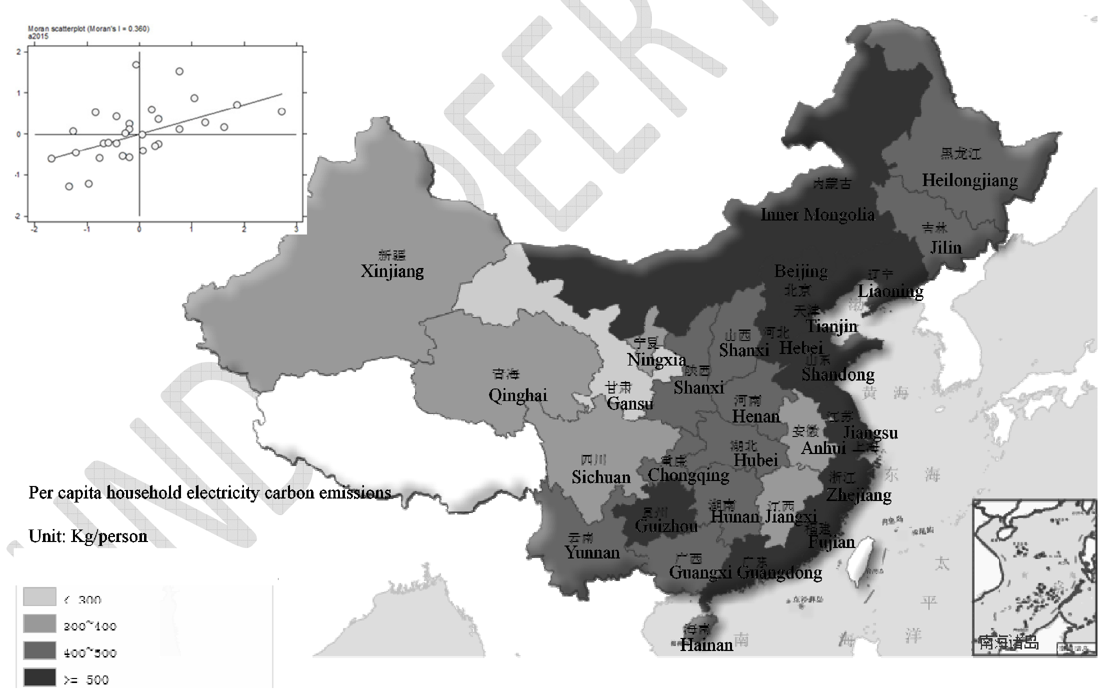

Fig.3 the distribution map and Moran scatter plot of per capita household electricity carbon emissions of Chinese residents in 30 province in 2015

4.2Spatial diagnostic test

To test which model could better fit the data, the non-spatial panel data model was first analyzed, and the classical Lagrange Multiplier Statistic (LM-lag, LM-error) and Robust Lagrange Multiplier Statistic (Robust

LM-lag, Robust LM-error) were used to select the spatial panel econometric model (Le Sage and Pace, 2009). The equation (1) was estimated by mixed OLS, space-fixed effect, time-fixed effect and space-fixed and time-fixed effect.

Due to the different situation of each province and city, there may be omission variables that do not change with time. The fixed effect is still the first choice for two reasons according to the current empirical analysis. This is because: firstly, when modeling spatial panel data, the fixed effect is usually more appropriate than the random effect. Secondly, Lee and Yu (2014) believed that the fixed effect was robust, and the calculation was as simple as the random effect model. Therefore, the fixed effect model is considered in this paper. The estimated results are shown in table 3.

Table 3 estimation results of non-spatial panel model

estimation method	mixed OLS	space-fixed	time-fixed	time-fixed and space-fixed
C	130.911***			
	(3.604)			
Lny	-39.806***	-5.310	-52.386***	-6.918
	(-3.677)	(-0.974)	(-5.599)	(-1.361)
$(\ln y)^2$	4.125***	0.663	5.283***	0.722
	(3.847)	(1.216)	(5.710)	(1.424)
$(\ln y)^3$	-0.140***	-0.024	-0.176***	-0.025
	(-3.949)	(-1.344)	(-5.785)	(-1.487)
lnUR	-0.052	1.060 ***	0.596***	1.232***
	(-0.505)	(6.710)	(5.686)	(7.805)
lnPD	0.033***	0.1496	0.0523***	-0.752
	(3.349)	(0.906)	(6.057)	(-3.733)
R^2	0.821	0.934	0.777	0.513
σ^2	0.036	0.006	0.026	0.005
D-W	1.620	1.873	2.132	2.003
Log-likelihood	82.318	370.039	136.258	396.110
LM spatial lag	59.453***	9.790***	0.298	0.467
	(p=0.000)	(p=0.002)	(p=0.585)	(p=0.495)
Robust LM spatial lag	15.528***	0.139	5.919**	10.776***
	(p=0.000)	(p=0.710)	(p=0.015)	(p=0.001)
LM spatial error	59.857***	19.812***	13.001***	1.971
	(p=0.000)	(p=0.000)	(p=0.000)	(p=0.160)

Robust LM spatial error	15.932*** (p=0.000)	10.160*** (p=0.001)	18.622*** (p=0.000)	12.280*** (p= 0.000)
per capita real GDP (Yuan) corresponding to the EKC minimum point	8604	——	5014	——
Real Per capita GDP (Yuan) corresponding to EKC maximum point	56954	——	67507	——

Note: lny represents the logarithm of carbon emissions generated by per capita household electricity consumption at the provincial level, lny represents the logarithm of per capita income at the provincial level, lnUR represents the logarithm of urbanization rate, lnPD represents the logarithm of population density at the provincial level, lnL represents the logarithm of maximum likelihood value, and D-W represents the statistic of Durbin-Waston. The estimated value of the explanatory variable is the corresponding t value in square brackets, and the corresponding p value in square brackets for each LM test statistic. ***, ** and * represent significant at the significance level of 1%, 5% and 10% respectively.

The estimation results of the non-spatial panel data model show that the estimation results of the time-fixed effect model are the best in this set of estimation methods. Since the estimators of independent variables and control variables of the time-fixed effect model are both significant at the significance level of 1%, the model fitting degree reaches 0.777, and the D-W statistic close to 2 indicates that the sequence correlation problem is not significant. Due to the introduction of the cubic form of regional per capita GDP in explanatory variables, the EKC curve estimated by the time-fixed effect model is of inverted N-shaped, and there are EKC minimum point and maximum point. The EKC minimum point corresponds to a per capita GDP of 5,014 Yuan (at constant price in 2005), while the EKC maximum point corresponds to a per capita GDP of 67,507 Yuan. The LM-lag and LM-error test results of the time-fixed effect model showed that the time-fixed effect model rejected the hypothesis that there was no spatial error term at the significance level of 1%, and whether there was a spatial lag term did not pass the test. Therefore, the spatial error model of time fixed effect was used for estimation next (seen in table 4).

Table 4 estimation results of spatial error model

Explanatory variables	Space error model of time - fixed effect
lny	-56.291*** (-5.951)
$(\text{lny})^2$	5.684*** (6.073)
$(\text{lny})^3$	-0.190*** (-6.151)
lnUR	0.529*** (5.116)
lnPD	0.051*** (5.219)

λ	0.302***
	(4.576)
σ^2	0.025
R^2	0.8705
corr-R^2	0.7765
log-likelihood	143.723
The per capita real GDP (Yuan) corresponding to the EKC minimum point	10198
Real Per capita GDP (Yuan) corresponding to the EKC maximum point	44355

From the estimation results of the spatial error model of time-fixed effect, the fitting degree R^2 of the spatial error model of time fixed effect was 0.875, which was higher than that of the non-spatial and time-fixed effect model, indicating that the spatial error model could better fit the data. The spatial error coefficient is 0.302 at the significance level of 1%, which again indicates that the household electricity carbon emissionshave a strong spatial autocorrelation. At the significance level of 1%, the logarithmic coefficients of per capita GDP are all significant, and the coefficients of the primary, secondary and tertiary terms are negative, positive and negative respectively, indicating that the Environmental Kuznets Curve of household electricity carbon emissions is of inverted N-shaped. The per capita real GDP of the maximum point and minimum point of EKC are 10198 Yuan and 44355 Yuan respectively.That means when per capita real GDP of the region is less than 10198 Yuan, per capita household electricity carbon emissions of residents are in a state of decline. When per capita real GDP of the region is between 10198 and 44355 Yuan, per capita household electricity carbon emissions are on the rise. When per capita real GDP of the region is greater than 44355 Yuan, per capita household carbon emissions are in a state of decline. In 2015, the per capita real GDP of 20 provinces (at constant price in 2005) was between 10198 and 44355 Yuan, and per capita real GDP of 10 provinces (at constant price in 2005) was above 44355 Yuan. Per capita household electricity carbon emissions are still rising in most of the provinces in China. Income is a key variable affecting residents' electricity consumption, and its influence on residents' electricity demand is mainly through the following two ways: first, indirectly affecting residents' electricity consumption by affecting their electric complementary-home appliances; second, through the impact of residents on the frequency of electrical appliances to produce a direct impact. At the same time, the coefficient of urbanization rate and population density is also significantly positive, indicating that the carbon emissions of household electricity will also increase with the acceleration of urbanization process and the increase of population. In the context of economic growth, accelerated urbanization and increasing population, reducing household carbon emissions from electricity can improve energy conservation and emission reduction.

5conclusion

This paper selects the panel data of 30 Chinese provinces from 2005 to 2015, and calculates the EKC of per capita household electricity carbon emissions through spatial error model. The main conclusions of this paper are as follows: according to the spatial statistical analysis and the estimation results of the spatial econometric model, there is a significant positive spatial autocorrelation between the householdelectricity carbon emissions of residents in various provinces or cities in China. Provinces and cities with high carbon emissions are usually adjacent to or surrounded by those with high carbon emissions, while those with low carbon emissions are usually adjacent to or surrounded by those with low carbon emissions. This is because the economic development level, population size and urbanization rate of neighboring provinces are similar. Therefore, in the theoretical summary, empirical test and formulation of energy-saving and emission reduction measures for household energy use, the impact of geographical space factors on carbon emissions from household energy consumption should be considered. When exploring the relationship between household electricity carbon emissions and income, the study shows that the per capita electricity carbon emissions and income of residents show an inverted N shape. At present, per capita household electricity carbon emissions of most provinces are in the rising stage, while that of some developed provinces are in the declining stage. The increase of urbanization rate and population growth will also lead to the increase of per capita household electricity carbon emissions. Therefore, under the trend of economic growth, increase of population size and acceleration of urbanization process, reducing household carbon emissions is still the key to energy conservation and emission reduction.

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