Nexus Among Energy Consumption Structure, Energy Intensity, Population Density, Urbanization And Carbon Intensity: A Heterogeneous Panel Evidence Considering Differences In Electrification Rates

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Nexus among energy consumption structure, energy intensity, population density, urbanization and carbon intensity: a heterogeneous panel evidence considering differences in electrification rates

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Abstract:

In this paper, the clustering method is used to divide the 30 provinces of the country into high, medium and low electrification rates according to the electrification rate from 2000 to 2017. The heterogeneous panel technology is used to analyze the relationship of energy consumption structure, energy intensity, population density, urbanization rate and carbon intensity. According to Cross-sectional dependence(CD) test and cross-section Im-Pesaran-

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Shin (CIPS) test results, the data of each panel are not in the form of same order single integer, so α convergence analysis, β absolute convergence, and β conditional convergence analysis are required. The results show that the carbon intensity of the four panels shows an α convergence; the β absolute convergence shows there is a "catch-up effect"; β conditional convergence indicates that the carbon intensity approaches their respective steady state levels; there is a long-term equilibrium relationship of energy consumption structure, energy intensity, population density and carbon intensity in all panels, but the urbanization rate has a significant impact on carbon intensity only in areas with high electrification rates. Finally, based on the results of empirical research, policy recommendations for reducing the carbon intensity in different regions are proposed.

Keywords: carbon intensity; electrification rate; heterogeneous panel analysis; convergence analysis

1 Introduction

China's economy has entered a new normal, developing to a higher level. The division of labor is clearer, and the growth rate has changed from high-speed growth to medium-high growth. China's economic development model is changing from extensive growth that focuses on scale and speed to intensive growth that focuses on quality and efficiency. The economic structure is changing from incremental expansion to stock adjustment, and the economic development momentum is changing from the traditional growth point to a new growth point. It is difficult to maintain a broad economic development model at the expense of environmental resources.

At the same time, in China's economic development and urbanization process, a large amount of energy consumption plays a key role, leading to increasing carbon emissions and increasing negative environmental impacts.

In 1991, American economists Grossman and Kruger’s negotiations on the North American Free Trade Area, Americans worried that free trade would worsen the Mexican environment and affect the domestic environment of the United States. They conducted the first empirical study on the relationship between environmental quality and per capita income, and put forward the EKC hypothesis(Grossman et al.1991). Soumyananda D explained the Environmental Kuznets Curve (EKC) hypothesis postulates an inverted-U-shaped relationship between different pollutants and per capita income, i.e., environmental pressure increases up to a certain level as income goes up; after that, it decreases(Soumyananda D.2004).

In early research, various environmental pollution indicators, cross-sectional data, and panel data to explore environmental issues related to economic development are used through dual empirical models to verify the EKC assumption, but no consistent conclusion was achieved. In China, output and carbon dioxide emissions are not just inverse relations(Lu H.2000). Azomahou and Van Phu used non-parametric research methods, showing that the relationship between carbon dioxide emissions and GDP is more complicated than the EKC curve(Azomahou et al.2001). Galeotti and Lanza used panel data to calculate the relationship between CO_2 emissions and GDP, and predicted emissions, believed that the empirical relationship between two variables is in a non-linear form, rather than the linear or logarithmic functions commonly considered(Galeotti M et al.1999).

However, more and more scholars have found that dual empirical models have the obvious defects in the description of the relationship between economy and environment. Therefore, researchers gradually added various factors to explore the relationship between GDP and CO_2 emissions from a variety of perspectives. Ma XJ and aims to quantify the relation between real GDP, CO_2 emissions, renewable and nonrenewable energy consumption, tourism development and labor force for France and Germany. Results reveal an inverted U-shape relation between CO2 emissions and real GDP in long run confirming the validity of environmental Kuznets curve for the group of France and Germany(Ma XJ et al.2021). Anser has identified the causality between GDP growth and carbon emission and found bidirectional causality between economic growth and energy use(Anser Muhammad Khalid et al.2021).

In addition, urbanization is an important factor in regard to the relationship between GDP and CO_2 emissions. For example, Wang Z investigates the dynamic interdependence between CO2 emissions, real gross domestic product (GDP), renewable and non-renewable energy generation, urbanization, and export quality for both the top ten renewable energy and top ten economic complexity index (ECI) countries (Wang Z et al.2021). Faisal investigates the association among carbon dioxide emissions, electricity consumption, capital, financial deepening and urbanization, the long-run effects identified the evidence of an inverted U-shaped association among carbon dioxide and urbanisation. This suggests that rapid urbanisation increases the levels of pollution in the initial stages of development(Faisal et al.2021). De uses parametric and semiparametric panel data analysis methodologies to test the hypothesis of the environmental Kuznets curve, in 186 countries in the period 1960-2019. The main results reveal the acceptance of this hypothesis in the relationships of CO2 emissions (kt) and economic growth (GDP) and urbanization (% population) in the parametric models(De et al.2021).

With the rapid economic development, carbon dioxide emissions have increased significantly, and environmental problems have become more and more serious. However， the total indicators have limitations in studying economic and environmental issues. Compared with the total index, the total index reflects the relative number of comprehensive changes in multiple items or variables, the carbon emission intensity index has more complex composition and influencing factors. Its form depends on the carbon emission coefficient of carbon-based energy, the composition of carbon-based energy, the proportion and energy intensity of carbon-based energy in total energy consumption, so that we can grasp timely and effectively the frontier areas and development trends of carbon emission intensity research. Many foreign scholars have begun to conduct research on carbon emission intensity. This research began in 1997. Reborts JT and Grimes PE compiled relevant data on the economic development and carbon emissions of several developed countries from 1965 to 1992 to verify carbon emissions. The correlation between intensity and national economic output, and the conclusion that both passed the "EKC curve" test, which opened the prelude to carbon emission intensity research(Roberts J T et al.1997).

The environmental pollution in China is affected by technological progress, economic growth, changes in industrial structure and the process of urbanization, as well as economic cycles and fluctuations, which is uncertain and hard to predict. In the past, studies were limited in the relationship between economic intensity and carbon intensity, but economic volatility in different cycles was relatively large. Carbon intensity was not easy to predict, and with economic development, the factors affecting carbon intensity became broader. Therefore, many domestic scholars have analyzed the influencing factors of carbon emission intensity.

In terms of influencing factors, Zhu and Zhang used the Logarithmic Mean Divisia Index (LMDI) model to analyze the influencing factors of energy intensity (EI) in Shanghai from 1995 to 2008(Zhu L et al.2011). The results show that the main influencing factor is the energy intensity of the industrial sector, followed by the energy structure adjustment and industrial structure adjustment. Gao of Lanzhou University analyzed the factors influencing the changes of carbon emissions in Sichuan Province from 2000 to 2011 through the LMDI model(Gao L et al.2014). Wang found that technological progress is not the main factor. By analyzing the spatial spillover effects and driving factors of carbon emission intensity in 283 cities across the country from 1992 to 2013, he found that the main influencing factors are also different in regions with different levels of carbon intensity(Wang S et al.2019).

Dong and Xu based on the multiplication and addition factor decomposition of the Mean Dirichlet Index (LMDI) to examine the impact of the four driving factors of energy intensity, internal energy structure, economic structure and external energy structure on the carbon intensity fluctuations in the production sector . The study found that energy intensity and internal energy structure are negative driving factors, while economic structure and external energy structure are positive driving factors(Dong M et al.2019). Based on perfect indicators and dynamic spatial panel model, Zhang F et al established a comprehensive framework to quantify the impact of industrial structure and technological progress on CI, and conducted empirical research on 281 prefecture-level cities in China from 2006 to 2016(Zhang F et al.2020).

In terms of panel data methods, Liu uses the LMDI factor decomposition method based on the energy consumption data of the power industry from 2000 to 2010, quantitative analysis of the differences in the carbon emission intensity of the power industry among 30 provinces and cities in China, and the contribution of various factors to reducing the carbon emission intensity of the power industry in China(Liu Y et al.2013). Wang believed that economic production, energy intensity, and industrial structure have a significant impact on carbon emissions, and the influence of population size and energy structure is limited. Wang and Zhang used logarithmic average weight Divisia decomposition method to construct a factor decomposition model of Beijing, Tianjin and Hebei's overall, regional, and industrial carbon intensity, and conducted an empirical analysis(Wang S et al.2017). Based on the statistical data of 30 provinces, municipalities and autonomous regions in China from 2004 to 2016, Feng , Zhang and Wang used Kernel density estimation method and LMDI factor decomposition method to study and analyze the dynamic evolution characteristics and main influencing factors of China's direct living energy consumption carbon intensity(Feng S et al.2018). On the basis of estimating the carbon intensity of each province, Liu Xianzhao, Gao Changchun and others used exploratory spatial data analysis (ESDA), spatiotemporal transition measurement methods and geographic weighted regression (GWR) models to analyze China's provinces from 1995 to 2017. The spatial dependence pattern of energy consumption, carbon intensity and the spatial heterogeneity of its driving factors(Liu X et al.2018).

By coordinating the progress of electrification on the power supply side, power consumption side and sustainable development level, it can promote the revolution of energy production and consumption, support the coordinated economic and social development, and promote the ecological environment. Therefore, the electrification rate is closely related to electricity, economy and environment. However, the existing research often ignores the factor of electrification rate. In addition, due to the significant heterogeneity of China's geographic map (Fei et al.2011, Zhang C et al.2012), this leads to deviations in traditional panel analysis techniques based on homogeneous panel data. Therefore, the heterogeneous panel analysis method should be used.

In summary, carbon emission from energy consumption is an inevitable by-product of economic development. Generally speaking, areas with large populations and high density have more carbon emission, which are also closely related to economic growth, so population density is related to carbon intensity. Moreover, energy intensity reflects the economy’s dependence on energy and is also related to carbon intensity to a certain extent. Furthermore, with the development of urbanization, urbanization rate has also become a potential factor affecting carbon emissions. Therefore, based on the regional diversity， this article mainly studies the relationship between electricity, economy, energy and the environment, through classifying 30 provinces by the electrification rate for energy-saving emission reduction policies.

The innovations of this article are as follows:

(1) At present, a new round of scientific and technological revolution has promoted the development of electrification into a new historical stage. The development of energy and

power is greener, the transmission and use of power is more intelligent, and the integration of energy and power with economic society and people's lives is closer, the power-centric energy transformation and upgrading is being accelerated. Therefore, the classification on 30 provinces in China based on the electrification rate is proposed to study the relationship between China's electricity, economy, energy and environment.

(2) According to the electrification rate of each province, 30 provinces in China are divided into three regions: high electrification rate, medium electrification rate and low electrification rate. In addition, heterogeneous panel technology is used to study the relationship between energy intensity, carbon intensity, energy consumption structure, urbanization rate and population density in different regions , which helps to formulate corresponding carbon emission reduction policies according to the characteristics of regional development.

(3) The heterogeneity between provincial panels in China is considered in this paper, so the heterogeneous panel analysis techniques are employed, including the CD cross-section correlation test and the second-generation unit root test CIPS test to ensure the validity of the results. Because the variables are non-homogeneous and simple integers in different panels, α convergence analysis, β absolute convergence analysis, and β conditional convergence analysis are performed for each variable in different panels.

The rest of the article is organized as follows: in Section 2, data resource, descriptive statistics of variables, and the model adopted in this paper are presented. In Section 3, the major econometric methodologies are proposed. In Section 4, the empirical findings and the interpretations of results are informed. In Section 5, the conclusions are summarized and some related policy remarks are proposed.

2 Proposed model, data and descriptive statistics

2.1 Proposed model and data

As suggested by previous studies(Wang S et al.2019, Abdeen Mustafa Omer.2007), urbanization, energy factors and economic growth have significant effects on CO_2 emissions. To further explore the interrelationships among energy intensity, urbanization rate, energy consumption structure, population density and carbon intensity, this paper proposes an expanded model where five representative variables are involved, shown as Eq.(1).

$$CI_{at} = f(UR_{at},\ ECS_{at}, PD_{at}, EI_{at}) \tag{1}$$

The subscripts a and t represent region and time period respectively (the time dimension is year) . *CI* means the carbon intensity (ten thousand tons / 100 million RMB),i.e., the CO_2 emission per unit of GDP. *UR* is the urbanization rate counted by proportion of urban population to the total population *ECS* reflects the structure of energy consumption, indicating that coal consumption accounts for the proportion of total energy consumption. *PD* means the population density (person / square kilometer). *EI* means the energy intensity, that is, energy consumed per unit of GDP (10,000 tons of standard coal / 100 million RMB). The data of province-level CO_2 emissions are obtained from China Emission Accounts and Datasets, and other data are collected from National Statistics Bureau. To reduce data fluctuations and eliminate the heteroscedasticity that may exist in the panel, the variables *PD* is converted in their natural logarithmic series, expressed as *LPD.* Since *CI, UR* and *EI* are percentage-typed variables, their coefficient can stand for the elasticity directly. According to previous related researches [Zhu Z et al.2017, Lotfalipour M R et al.2010, Arouri M E H et al.2012], the logarithmic linear function is constructed as bellow:

$$CI_{at} = \beta_{1a}UR_{at} + \beta_{2a}ECS_{at} + \beta_{3a}LPD_{at} + \beta_{4a}EI_{at} + u_{ab} \tag{2}$$

where β_{1a}, β_{2a}, β_{3a} and β_{4a} are elasticities of *CI* with pertain to *UR*, *ECS*, *LPD* and *EI* per province, respectively. μ_{ab} is the error with a mean of 0 and a variance of σ^2.

2.2 Cluster analysis

We use a balanced panel of 30 provinces in China, namely, Tianjin (TJ), Beijing (BJ), Shanghai (SH), Inner Mongolia (IM), Shandong (SD), Chongqing (CQ), Hubei (HuB), Jiangsu (JS) , Jilin (JL), Shaanxi (SX1), Liaoning (LN), Ningxia (NX), Hunan (HuN), Guangdong (GD),Hainan (HaiN), Qinghai (QH), Hebei (HeB), Henan (HeN), Xinjiang (XJ), Zhejiang (ZJ), Heilongjiang (HLJ), Jiangxi (JX), Sichuang (SC), Anhui (AH), Guangxi (GX), Shanxi(SX2), Guizhou(GZ) , Yunnan (YN) and Gansu (GS), Fujian (FJ), covering the period from 2000 to 2017.

As socialism with Chinese characteristics enters a new era, accurately grasp the level of electrification development in various regions of our country, deeply analyze the development potential of electrification, scientific planning, policy guidance, and key advancement, and continuously improve the level of electrification in China. This is an important way to promote high-quality economic development and the process of low-carbon energy and electricity.

Table 1 The provinces in different areas

Panel	**Provinces**

HERR	BJ,NMG,SH,AH,JX,SD,HeN,GX,HaiN,GZ,YN,SX1,GS
MERR	JS,ZJ,FJ,GD,QH,NX
LERR	TJ,HeB,SX2,LN,JL,HLJ,HuB,HuN,CQ,SC,XJ

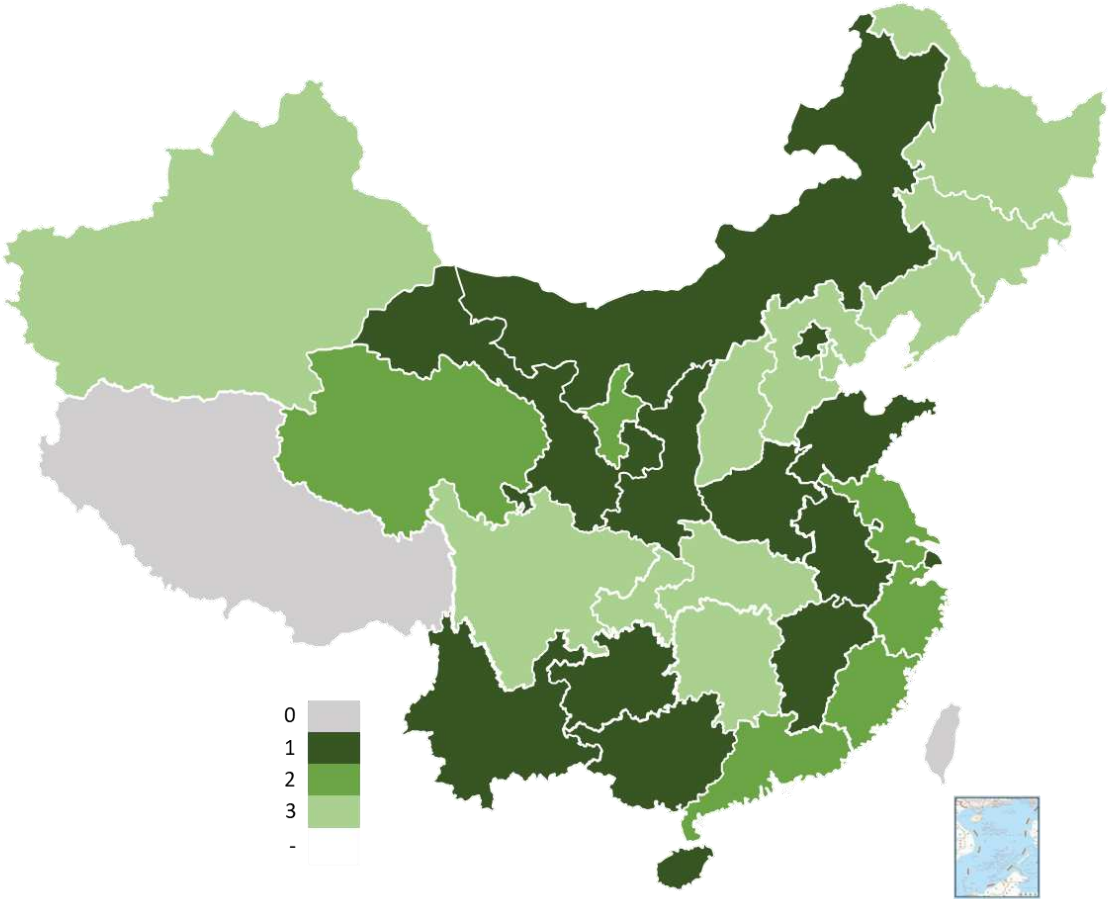

Figure 1 Geographical distribution of electrification rate

According to the k-means cluster analysis, 30 provinces are divided into three categories according to the electrification rate (the proportion of electricity consumption in energy consumption): high electrification rate area, medium electrification rate area and low electrification rate area, which are represented by HERR, MERR, and LERR respectively. The cluster analysis is shown in Table 1 and Fig. 1. In Fig.1, 1, 2, and 3 represent HERR, MERR, LERR respectively, and the gray area indicated by 0 is the area not considered in this research.

2.2 Descriptive statistics of variables

Before conducting econometric model testing, we need to observe the changing trends of variables in each province and each period. The trend chart is as follows, in the three-dimensional graph, the x-axis is the province, the y-axis is the year, and the z-axis is the value of each variable. The color changes from blue to yellow, indicating that the value is from small to large. In the plane trend graph, the horizontal axis represents the province and the vertical axis represents the year, the color changes from blue to yellow, which also represents the variable value from small to large.

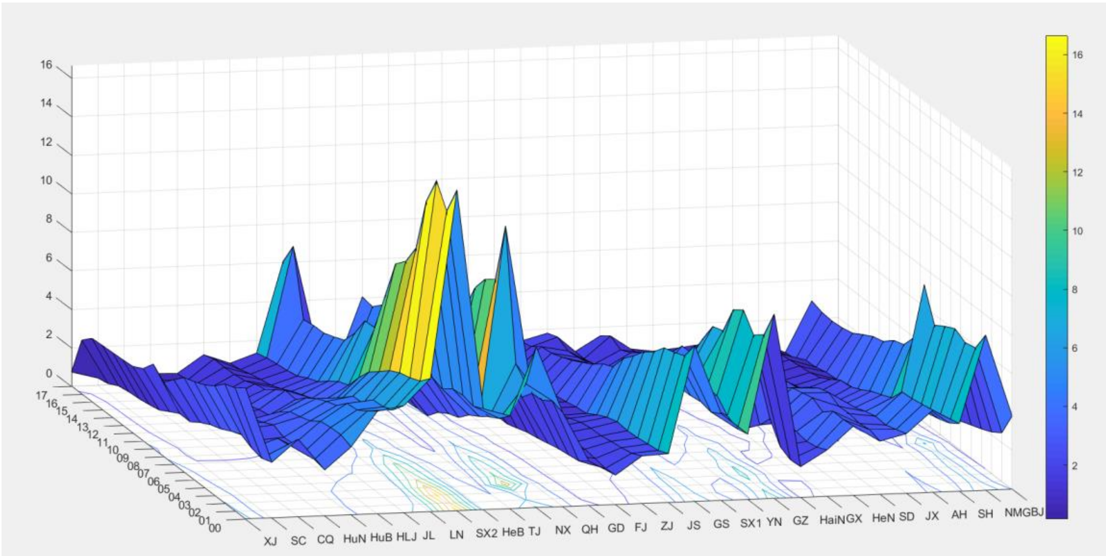

Figure 2 the three-dimensional trend graph of CI

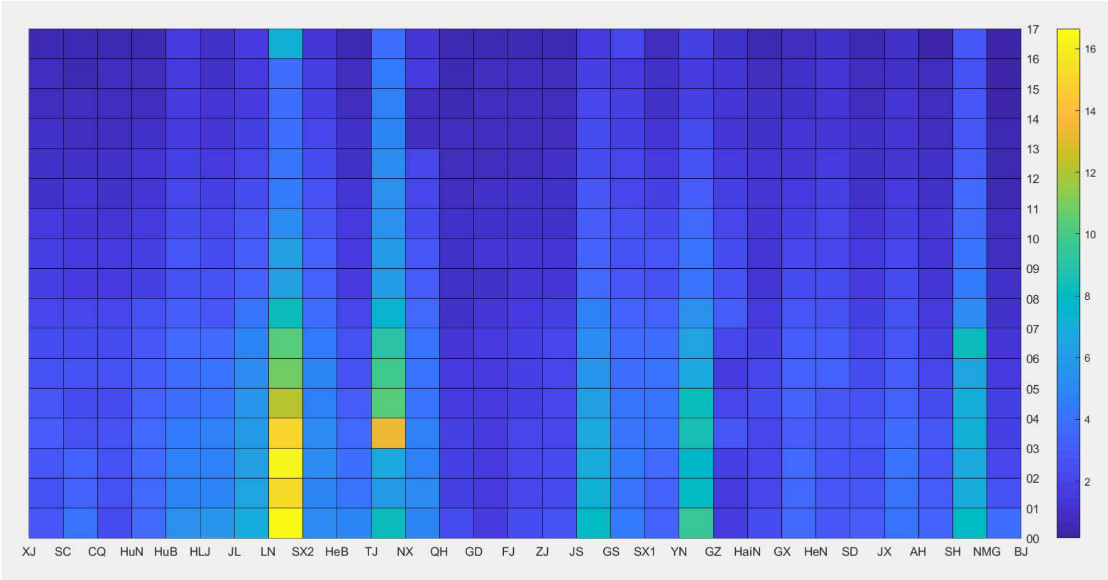

Figure 3 the plane trend graph of CI

Figures 2 and 3 show the three-dimensional trend graph and the flat trend graph of the CI in each province from 2000 to 2017. It can be found that the color changes in the figure are more obvious, indicating that CI has significant differences in the same period in different provinces.

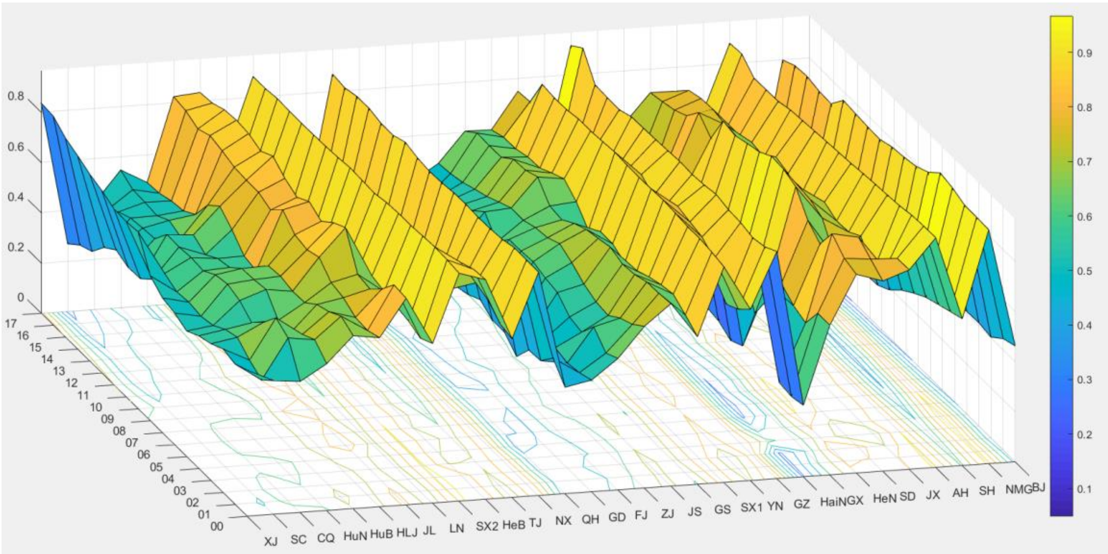

Figure 4 the three-dimensional trend graph of ECS

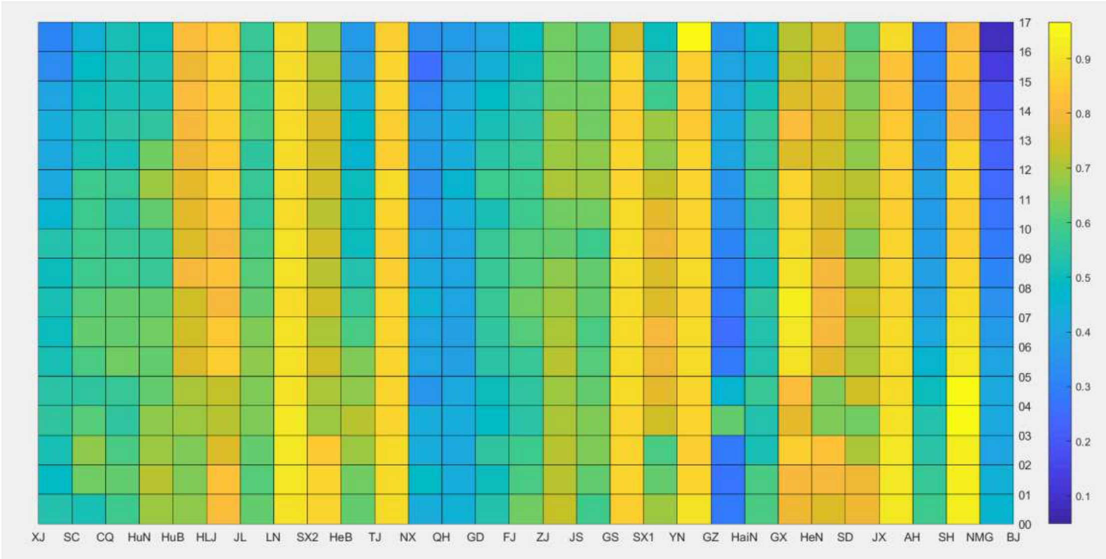

Figure 5 the plane trend graph of ECS

Figures 4 and 5 show the three-dimensional trend graph and the flat trend graph of the ECS in each province from 2000 to 2017. It can be found that the color changes in the figure are obvious, indicating that ECS has significant differences in the same period in different provinces.

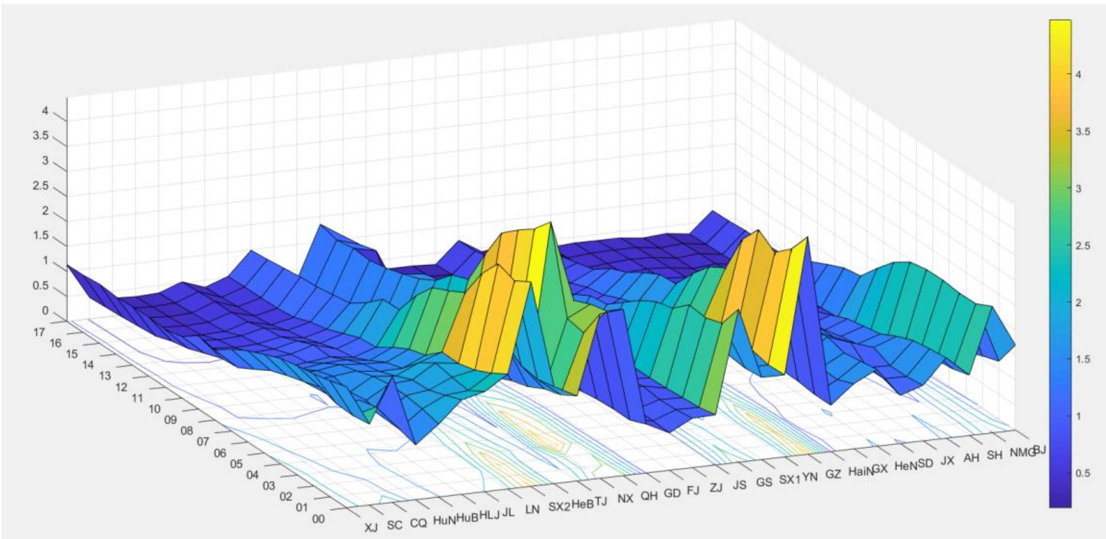

Figure 6 the three-dimensional trend graph of EI

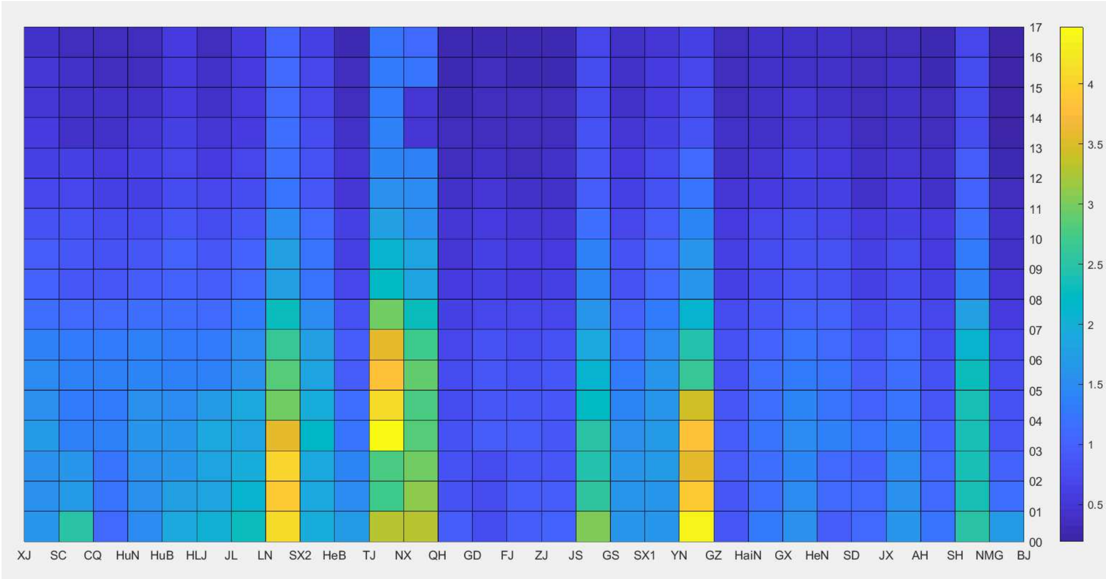

Figure 7 the plane trend graph of EI

Figures 6 and 7 show the three-dimensional trend graph and the flat trend graph of the EI in each province from 2000 to 2017. It can be found that the color changes in the figure are more obvious, indicating that EI has significant differences in the same period in different provinces.

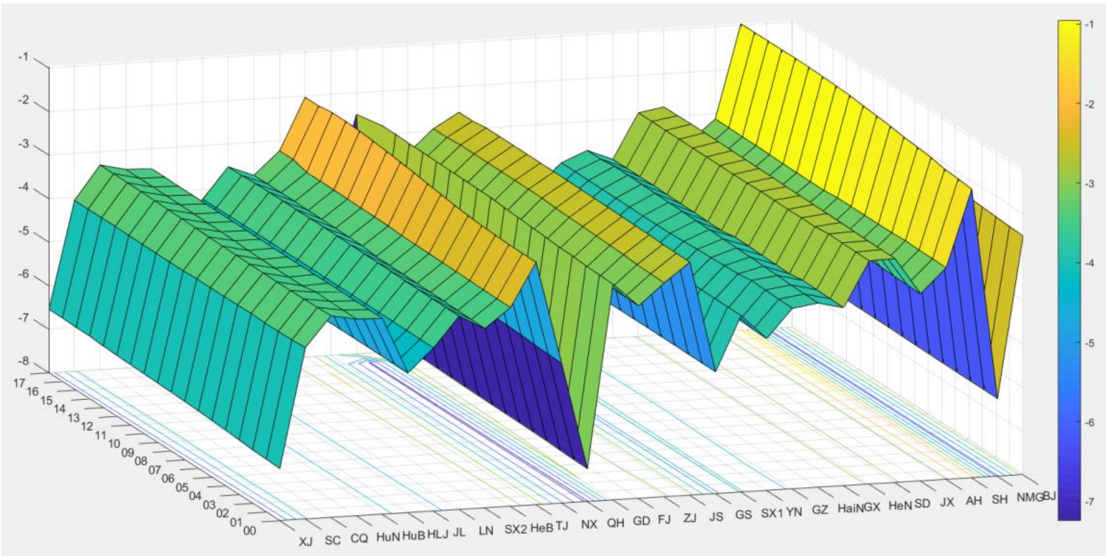

Figure 8 the three-dimensional trend graph of LPD

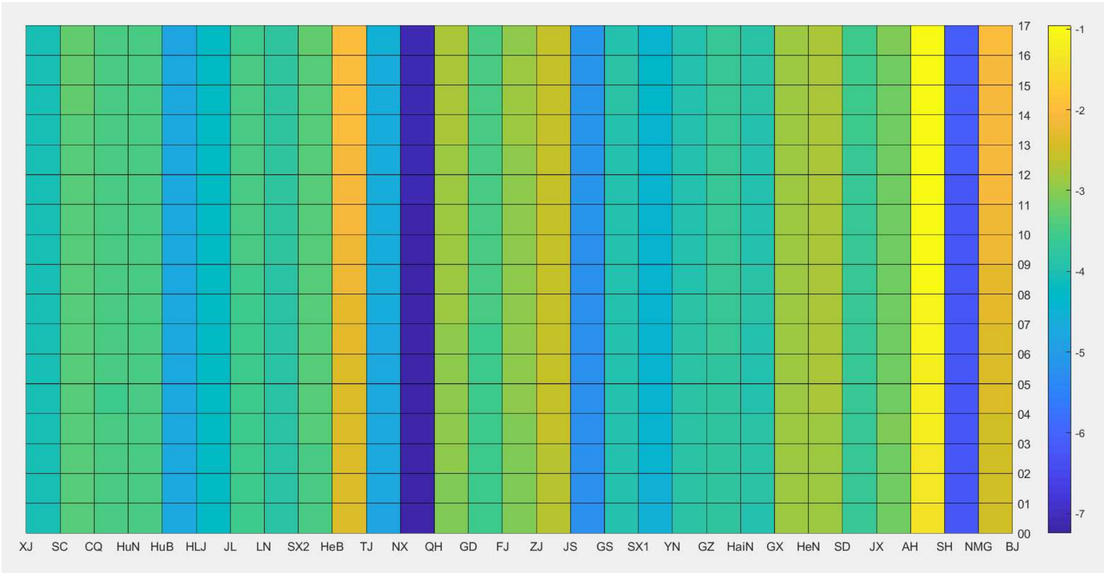

Figure 9 the plane trend graph of LPD

Figures 8 and 9 show the three-dimensional trend graph and the flat trend graph of the LPD in each province from 2000 to 2017. It can be found that the color changes in the figure are obvious, indicating that LPD has significant differences in the same period in different provinces, but the population in each province is relatively stable

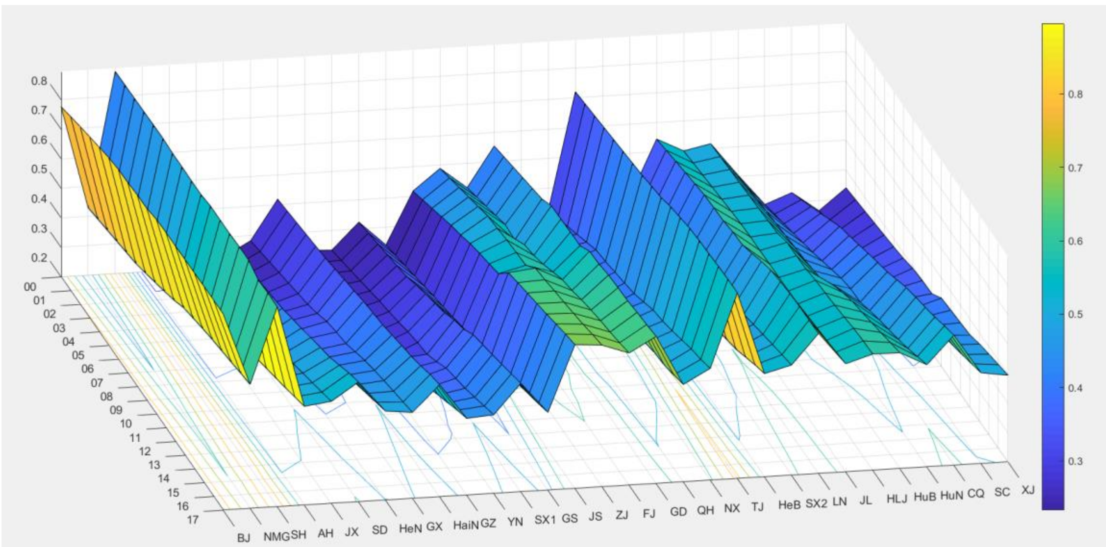

Figure 10 the three-dimensional trend graph of UR

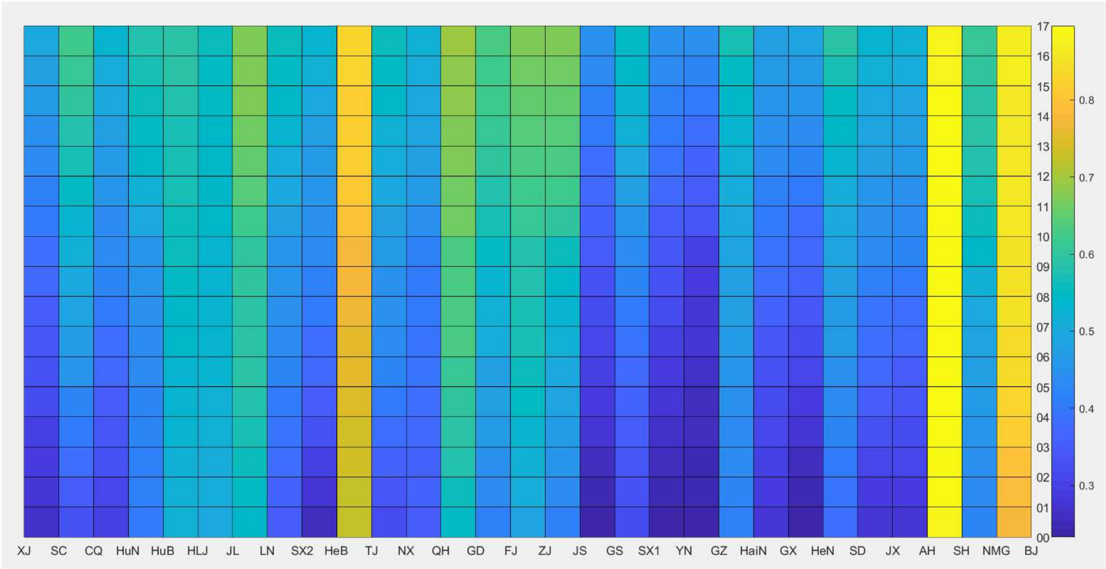

Figure 11 the plane trend graph of UR

Figures 10 and 11 show the three-dimensional trend graph and the flat trend graph of the UR in each province from 2000 to 2017. It can be found that the color changes in the figure are more obvious, indicating that UR has significant differences in the same period in different provinces.

In summary, all variables have inter-provincial differences and meet the requirements of measurement research

Table 2 shows the descriptive statistics of all variables in the national horizontal panel and the three sub-panels. Including mean, median, maximum, minimum, standard deviation, skewness and kurtosis.

Table 2 Descriptive statistics for all variables in panel and cross-sections

Objects	Variables	Mean	Median	Max.	Min.	Std.Dev.	Skewness	Kurtosis
Nation	CI	2.8040	2.1669	16.6536	0.1546	2.2729	2.3578	11.5715

	LPD	-3.7795	-3.5664	-0.9543	-7.2422	1.2587	-0.7756	4.0326
	EI	1.1056	0.9110	4.4755	0.1920	0.7643	1.6896	6.3770
	ECS	0.6447	0.6438	0.9671	0.0491	0.1860	-0.3349	2.3580
	UR	0.5008	0.4806	0.8960	0.2330	0.1521	0.7968	3.3786
HERR	CI	2.6085	2.1569	8.5584	0.1546	1.7734	1.4021	4.7450
	LPD	-3.6109	-3.6851	-0.9543	-6.2121	1.2338	-0.0578	3.2066
	EI	1.0181	0.8353	4.3532	0.1920	0.6976	1.8865	7.6041
	ECS	0.6685	0.7191	0.9671	0.0491	0.2133	-0.7126	2.4964
	UR	0.4812	0.4395	0.8960	0.2330	0.1863	1.0786	3.2017
MERR	CI	2.4778	1.5989	13.4085	0.3675	2.3730	2.0680	7.7346
	LPD	-3.9211	-3.0765	-2.4986	-7.2422	1.5641	-1.2415	3.1347
	EI	1.1354	0.8386	4.4755	0.2709	0.9806	1.5959	4.7227
	ECS	0.5725	0.5502	0.8920	0.2606	0.1728	0.5022	2.1836
	UR	0.5357	0.5396	0.6985	0.3253	0.0982	-0.2007	2.0110
LERR	CI	3.2128	2.5839	16.6536	0.3842	2.6617	2.5492	11.9038
	LPD	-3.9016	-3.5207	-1.9885	-6.7999	1.0702	-1.1940	4.7036
	EI	1.1928	1.1248	4.0972	0.3025	0.6951	1.4054	6.1314
	ECS	0.6560	0.6396	0.9172	0.2688	0.1447	0.0087	2.3562
	UR	0.5048	0.5056	0.8292	0.2622	0.1260	0.5964	3.1949

In table 3, by referring to the P-value<1%, presents the correlations among the analyzed variables for national level, which indicates that *CI* have significant positive correlations with

ECS and *EI*, and have significant negative correlations with *UR* and *LPD*. With the increase of urbanization rate and population density, the efficiency of public infrastructure is improved, and the contribution of resource utilization efficiency to economic growth is greater than that of carbon emission, which leads to the decrease of carbon intensity. Besides, the results also show that UR has negative correlations with ECS, indicating that a low energy efficiency is harmful to urbanization. And coal consumption is still a significant element promoting GDP and *UR*.

Table 3 Correlations for the panel data set (p values in parentheses)

Correlation Probability	CI	LPD	EI	ECS	UR
CI	1.0000				
LPD	-0.358878 (0.0000) ***	1.0000			
EI	0.909450 (0.0000)***	-0.436085 (0.0000) ***	1.0000		
ECS	0.499894 (0.0000)***	-0.210544 (0.0000)***	0.366141 (0.0000) ***	1.0000	
UR	-0.415299 (0.0000)***	0.506431 (0.0000)***	-0.511260 (0.0000) ***	-0.463933 (0.0000)***	1.0000

Note: *** Denotes statistical significance at 1% level.

3 Econometric methodologies

3.1 Cross-sectional dependence test

That is worth noting that the cross-sectional dependence across provinces could exist due to the macroeconomic strategy at the provincial level such as the policy of reform and opening, the western development strategy and the strategy of rise of central plains area. Thus, it is important to verify whether cross-sectional correlation exists before the empirical analysis. According to existing studies(Pesaran M H .2007,De Hoyos et al.2006), this paper assume that standard represent the model：

$$Y_{at} = \alpha_a + \beta_{at} X_{at} + \mu_{at}, \qquad a = 1,2,\dots,A, \quad t = 1,2,\dots,T \tag{3}$$

The null hypothesis without cross-sectional dependence is H_0: $\rho_{ad} = \rho_{da} = cor(\mu_{\mathrm{at}}, \mu_{\mathrm{dt}}) = 0$ for any $a \neq d$, and the alternative hypothesis is H_1: exist $a \neq d$ making $\rho_{ad} = \rho_{da} = cor(\mu_{\mathrm{at}}, \mu_{\mathrm{ta}}) \neq 0$, where ρ_{ad} is calculated as follow:

$$\rho_{ad} = \sum_{t=1}^{T} \mu_{at}\mu_{dt} \Big/ \sqrt{\sum_{t=1}^{T} \mu_{at}^2 \sum_{t=1}^{T} \mu_{dt}^2} \tag{4}$$

$$CD = \sqrt{\frac{2T}{A(A-1)}} \sum_{a=1}^{A-1} \sum_{d=a+1}^{A} \hat{\rho}_{ad} \to N(0,1) \tag{5}$$

3.2 Panel unit root test

It is essential performing a unit root test to determine the stability of variables to prevent false regression. According to existing studies(Levin A et al.2002, Breitung J.2001), unit root tests models are widely used for panel unit root tests. However, for panels with cross-sectional dependencies, the first-generation unit root test tends to over-reject the null hypothesis(Pesaran M H.2007, Bhattacharya M et al.2016). Thus, the cross-section Im-Pesaran-Shin (CIPS) method developed by Pesaran(Pesaran, M H,2004) is adopted, using average individual statistics as follows::

$$\Delta z_{at} = \alpha_a + \beta_a^* z_{a,t-1} + c_0 \bar{y}_{t-1} + c_1 \Delta \bar{z}_a + \mu_{at} \tag{6}$$

where $\bar{z}_a = N^{-1} \sum_{a=1}^{N} z_{ab}$ and Δ represents the difference operator. Considering the serial correlation in the data, the model can be extended as follows:

$$\Delta z_{at} = \alpha_a + \beta_a^* z_{a,t-1} + c_0 \bar{z}_{a-1} + \sum_{d=0}^{r} c_{d+1} \Delta \bar{z}_{t-d} + \sum_{k=1}^{r} b_k \Delta z_{a,t-k} + \mu_{at} \tag{7}$$

where r is the lagged order determined by AIC and SIC. For each a, the extended CADF regression is performed according to (7), and then the t statistic of β_i^* is obtained.

$$CIPS = A^{-1} \sum_{a=1}^{A} CADF_a \tag{8}$$

3.3 Convergence analysis method

The economic convergence is further classified based on the neoclassical economic growth theory, and the test model is put forward accordingly. Convergence analysis can be divided into the following three categories:

3.3.1 α convergence,

This paper, the compiler coefficient method in the α convergence model is used to evaluate the development trend of the absolute gap of carbon emission efficiency in regions with different electrification rates in selected 30 provinces.

$$\overline{X} = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{9}$$

$$\alpha = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} \left(X_i - \overline{X} \right)^2} \tag{10}$$

X_i is the carbon emission intensity of the year under a certain electrification rate level, $\overline{X}$ is the mean value of carbon intensity, and α is the standard deviation. If the standard deviation shows a decreasing trend in time series, the carbon emission efficiency during this period is α Convergence.

3.3.2 β absolute convergence

The purpose of β absolute convergence is to judge whether the low carbon emission intensity has a tendency to move toward high carbon emission intensity, that is, to judge whether there is a “catch-up effect”. If there is a “catch-up effect”, it means that the carbon emission intensity situation at the electrification rate level is developing towards a good trend. The β absolute convergence model is shown below.

$$\Delta CI_i = \alpha + \beta CI_{i,t} + \mu_{i,t} \tag{11}$$

Where $CI_{i,t}$ indicates the carbon emission intensity at a certain electrification rate level in a certain year ΔCI_i indicates the difference between the carbon emission intensity at the electrification rate level of t+1 and t years. α is a constant term. $\mu_{i,t}$ is an error term. When β <0, the results pass the significance test, it is proved that there is the” catch-up effect” on the carbon emission intensity at the electrification rate level.

3.3.3 β conditional convergence

The purpose of β conditional convergence is to judge whether the regional carbon emission intensity of different electrification rate levels is close to their respective steady-state levels , whether each influencing factor has a positive or negative inhibition effect on the carbon emission intensity. The β conditional convergence model is as follows.

$$\Delta CI_i = \alpha + \beta CI_{i,t} + \lambda X_{\mathrm{i}} + \mu_{i,t} \tag{12}$$

Where $CI_{i,t}$ indicates the carbon emission intensity at a certain electrification rate level in a certain year ΔCI_i indicates the difference between the carbon emission intensity at the electrification rate level of *t+1* and *t* years. α is a constant term. $\mu_{i,t}$ is an error term. x_i is the control variable.

4 Empirical findings and interpretations

4.1 Cross-sectional dependence test

The results of cross-sectional dependence test is presented in Table 4. It can be seen that five variables, i.e., *CI*, *LPD*, *EI*, *UR* and *ECS,* reject the null hypothesis in all panels within ten percent, which indicates that the cross-sectional dependence exists. Therefore, the second generation of panel unit root detection technology is introduced.

Table 4 Pesaran cross-sectional dependence test results

Region	Variable	CI	LPD	EI	ECS	UR	Overall
Nation	Pesaran CD test	15.14808	10.5524	15.82276	19.18348	4.907672	-1.899475
	Prob.	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0575*
HERR	Pesaran CD test	-2.903043	-3.03014	-2.87702	-2.921711	-2.997068	-2.178282
	Prob.	0.0037**	0.0024***	0.0040***	0.0035***	0.0027***	0.0294**
MERR	Pesaran CD test	15.09503	14.49743	14.4493	15.43831	15.29589	7.598773

	Prob.	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
LERR	Pesaran CD test	-2.920068	-3.055308	-2.829178	-2.122584	-3.025633	-2.36103
	Prob.	0.0035***	0.0022***	0.0047***	0.0338**	0.0025***	0.0182**

Notes: ***, **,*Denotes the rejection of null hypothesis at 1%, 5%, 10% significance level.

4.2 Panel unit root test

As described above, because the existence of cross-sectional dependence makes results of first generation panel unit root test methods biased, recently developed second generation panel unit root test technique named CIPS test is adopted in this section to inspect stationarity with *CI, LPD, EI, ECS* and *UR*. Results of the panel unit root test is presented in Table 5, indicating that all variables are non-stationary at stage that are non-stationary at their first difference.

Table 5 Panel unit roots results

Region	**CIPS test**	**Variable**					**Criterion**		
		CI	**LPD**	**EI**	**ECS**	**UR**	**10% level**	**5% level**	**1% level**
Nation	Level	-1.705	-0.58	-3.051***	-2.092	-1.643	-2.11	-2.2	-2.38
	1st diff.	-3.558***	-0.958	-	-3.608***	-2.334	-2.11	-2.2	-2.38
HERR	Level	-1.792	-1.189	-2.735***	-1.984	-1.459	-2.11	-2.22	-2.45
	1st diff.	-3.495***	-2.901***	-	-3.678***	-2.748**	-2.22	-2.4	-2.76

MERR	Level	-2.106	-0.218	-2.091	-2.286*	-1.683	-2.18	-2.33	-2.64
	1st diff.	-3.844***	-0.732	-4.221***	-4.167***	-3.611***	-2.15	-2.29	-2.56
LERR	Level	-2.459***	-1.661	-3.364***	-2.138*	-2.311**	-2.11	-2.22	-2.45
	1st diff.	-	-2.983***	-	-3.637***	-	-2.11	-2.22	-2.45

Notes: * CIPS test is estimated applying constant and trend with 1 lag.

***, **, *Denotes the rejection of null hypothesis at 1%, 5%, 10% level of significance.

4.3 Convergence analysis results

4.3.1 α convergence results

In this paper, the carbon intensity from 2000 to 2015 has been tested for α convergence, and the standard deviation of each year is shown in Table 6 at the level of Nation, HERR, MERR and LERR:

Table 6: standard deviation under Nation, HERR, MERR, LERR level

Year	Nation	HERR	MERR	LERR
2000	3.018154	2.774374	2.934958	3.638367
2001	2.996758	2.616011	2.698242	3.432976
2002	3.009933	2.707337	2.717034	3.497186
2003	3.110857	2.763777	3.478131	3.336141
2004	2.874087	2.678702	3.05058	3.045049
2005	2.771108	2.556362	3.002436	2.93052
2006	2.716868	2.571348	2.896845	2.831414

2007	2.48737	2.339352	2.662771	2.602084
2008	2.290414	2.176027	2.451697	2.372895
2009	2.276582	2.155688	2.428462	2.370804
2010	2.178551	2.073204	2.335825	2.251123
2011	2.114532	2.006879	2.317713	2.162923
2012	2.073267	1.961625	2.281376	2.122359
2013	2.022632	1.914733	2.201831	2.082521
2014	1.995876	1.885246	2.164931	2.06381
2017	1.98808	1.871111	2.178626	2.051068
2016	2.023763	1.858509	2.129298	2.183571
2017	1.898822	1.843966	1.746923	2.066937

In order to observe the trend of standard deviation in time series more intuitively, the above table is converted into chart form, as shown in figure 12.

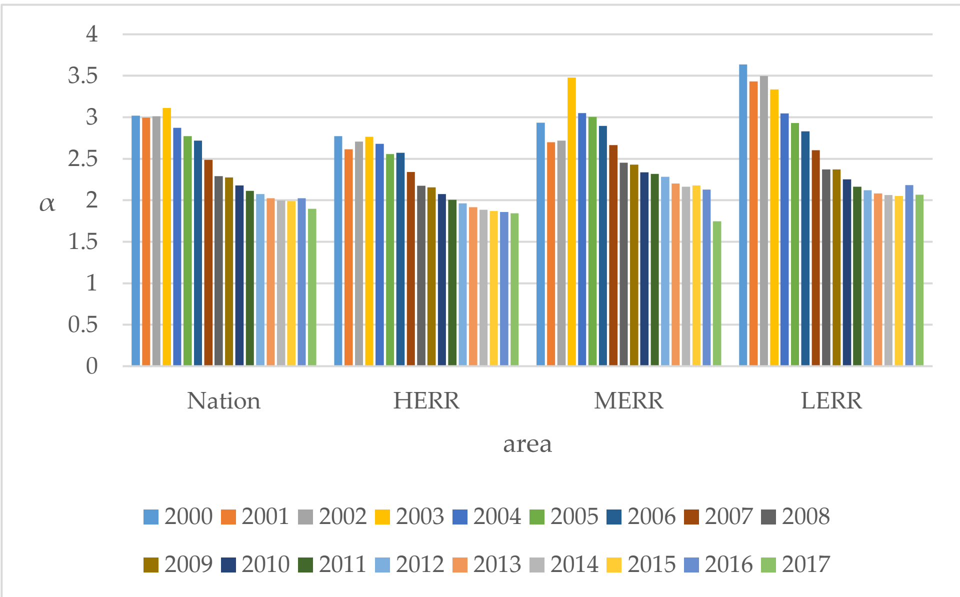

Figure 12 development trend of carbon emission intensity standard deviation in time series.

As shown in Figure 12 the overall trend in each region is a downward trend, but not a monotonous decline, indicating that China's carbon emission control level has significantly improved and the carbon emission intensity has continued to decline.

The HERR panel data is lower than the national level as a whole, while LERR is higher than the national level as a whole.

This is mainly due to the mature economic development in areas with high electrification rate and relatively stable economic growth. The energy structure transformation process is relatively fast, and the energy consumption structure is relatively optimized. Therefore, the degree of fluctuation of carbon intensity is small. In areas with low electrification rates, the energy structure is still dominated by coal power, the transformation of the energy structure is intensified, and economic growth is also fast, so the volatility of carbon intensity is relatively high.

The overall degree of fluctuation in various regions tends to decline, but the carbon emission intensity increased significantly in 2003, which requires further study.

4.3.2 ✈ absolute convergence results

Table 7:◎◎absolute convergence results

Region	LS				
	Coefficient	Std. Error	t-Statistic	Prob.	R-squared
Nation	-0.6765	0.0403	-16.7839	0.0000	0.3567
HERR	-0.8168	0.0686	-11.9146	0.0000	0.3933

MERR	-0.7245	0.0470	-15.4176	0.0000	0.3188
LERR	-0.5587	0.0698	-8.0000	0.0000	0.2570

As can be seen from Table 7, coefficient are all negative in the regression results of Nation, HERR, MERR, and LERR panels, and the P value is less than 0.01,which indicates there is a "catch-up effect " in the carbon intensity under the horizontal panel of each electrification rate, the carbon intensity is absolutely convergent.

4.3.3 β conditional convergence results

Table 8: β conditional convergence results

Region	Variable	LS			
		Coefficient	Std. Error	t-Statistic	Prob.
Nation	CI	-0.9976	0.1076	-9.2750	0.0000
	LPD	0.3803	0.0839	4.5351	0.0000
	EI	1.6134	0.3187	5.0626	0.0000
	ECS	-3.6350	0.6088	-5.9707	0.0000
	UR	-2.024382	0.7666	-2.6408	0.0085
	R-squared	0.4735			
HERR	CI	-2.0125	0.1140	-17.6478	0.0000
	LPD	-0.3297	0.0541	-6.0925	0.0000
	EI	3.4861	0.2741	12.7181	0.0000
	ECS	-1.5924	0.3709	-4.2929	0.0000

	UR	-1.998095	0.3128	6.3878	0.0000
	R-squared		0.6486		
MERR	CI	-2.1198	0.0972	-21.8156	0.0000
	LPD	-0.3977	0.0501	-7.9455	0.0000
	EI	3.7124	0.2331	15.9279	0.0000
	ECS	-2.9422	0.4609	-6.3837	0.0000
	UR	2.1159	0.4323	4.8948	0.0000
	R-squared		0.8198		
LERR	CI	-1.9640	0.1542	-12.7404	0.0000
	LPD	0.8545	0.1331	6.4199	0.0000
	EI	5.3668	0.5619	9.5514	0.0000
	ECS	5.5659	1.0856	5.1270	0.0000
	UR	-0.8567	0.9085	-0.9430	0.3469
	R-squared		0.511888		

As can be seen from Table 8, in the β conditional convergence regression results, β <0 and passed the significance test, that is, in regions with different levels of electrification rates, the carbon intensity approaches their respective steady-state levels. The energy consumption structure, population density, energy intensity will positively promote carbon intensity, while the urbanization rate in the HERR panel has a negative inhibitory effect on carbon intensity at the level of 10%. In other panels, the urbanization rate does not affect carbon intensity significant impact.

5 Conclusions and policy implications

As the largest carbon dioxide emitter, China has solemnly promised to reduce carbon emissions. However, as a developing country, china‘s task of reducing carbon is arduous， because a large amount of fossil energy is necessary to fuel the rapid economic development. It should be noted that different levels and methods of economic development in different regions of China make it difficult to implement a unified carbon reduction policy. In addition, the acceleration of China's urbanization process also has an impact on carbon intensity, and this effect is different in various regions. Therefore, in the context of urbanization, exploring the factors that affect the carbon intensity in different regions of China is theoretically and practically important.

Data clustering based on the electrification rate is employed in this paper to classify 30 provinces of China into three regions. The heterogeneous panel analysis technology and α, β convergence analysis are used to examine the relationship between energy intensity, energy consumption structure, population density, urbanization rate and carbon intensity. These results obtained adopted a more objective approach to reveal the factors that affect the carbon intensity of China's current socio-economic environment and provided theoretical basis and empirical support for the formulation of carbon reduction policies targeted at different regions.

This paper uses heterogeneous panel technology and convergence analysis technology to study the influencing factors of regional carbon intensity in China. Main findings are as follows:

(1) According to the results of α convergence analysis and β convergence analysis, in Nation,

HERR, MERR and LERR panels, the carbon intensity is in an α-convergence situation, which indicates that there is a "catch-up effect". Also, it approaches the respective steady-state levels. This means that the national electrification development has become more balanced, and the level of electrification in Nation panel will continue to increase. The electrification process will more effectively promote the green and low-carbon transformation of energy and power development, and provide strong supports for economy development.

(2) The result of β-condition convergence shows that in the heterogeneous panels, there is a long-term equilibrium relationship between carbon intensity and population density, energy intensity, and energy consumption structure. In the national panel, population density and energy intensity all have a positive effect on the growth of carbon intensity. Among them, energy intensity plays a more significant role, while the urbanization rate and energy consumption structure have a significant inhibitory effect on the growth of carbon intensity. In areas with high and medium electrification rates, energy intensity promotes the growth of carbon intensity most significantly, followed by urbanization rate, and energy consumption structure has a significant inhibitory effect on the growth of carbon intensity. In areas with low electrification rates, energy consumption structure and energy intensity have a significant role in promoting carbon intensity growth, but population density has an inhibitory effect on carbon intensity growth. The main reason for this is that regions with higher electrification levels have more advanced energy-saving and emission-reduction technologies. Energy-saving and emission-reduction technologies have improved energy efficiency, thereby reducing energy consumption and suppressing carbon intensity.

(3) It can be seen from the result of β condition convergence that the impact of urbanization rate on carbon intensity has significant spatial differences in different regions. It has a significant inhibitory effect on carbon intensity in high-electrification areas, and promotes the growth of carbon intensity in medium-electrified areas, but has no significant effect on carbon intensity in low-electrification areas. The reason is that at non-contemporaneous levels, in areas with high electrification rates, with the increase in urbanization rates, the transformation of the energy structure has become more and more intensified. Therefore, in areas with high electrification rates, the rate of urbanization affects carbon intensity has an obvious negative inhibitory effect. However, areas with low and medium electrification rates are still characterized by the traditional economic development mode of "three highs and one low", that is, the economic growth model of high input-high consumption-high pollution-low efficiency, which will bring serious negative impacts on the environment harmony and ecology. The energy structure of the MERR region is still dominated by coal, and the second energy model based on oil and gas has not been completed yet, and it is facing the third wave of energy revolution represented by the change in energy utilization mode (Stan.2018). in this context, the urbanization rate has a significant role in promoting carbon intensity.

Thirty selected provinces of China are divided into three sub-panels (high electrification rate, medium electrification rate and low electrification rate) according to the electrification rate standard in this paper, rather than based on geographical location in the conventional models. Through empirical analysis, the results of each sub-panel are different from those of the national panel. This result fully considers the regional differences in China and can more comprehensively reflect the relationship between regional carbon intensity, population density, energy consumption structure, energy intensity and urbanization at different levels of economic development. This will provide an empirical reference for the formulation of energy, economic and environmental policies that are more in line with the actual conditions of each region. This is also the practical value of this article.

Based on the finds in this paper, the following policy recommendations for reducing carbon intensity can be proposed:

(1) In regard to the areas with high electrification rates, the empirical results show that energy intensity has the greatest promotion effect on carbon intensity, and energy consumption structure has a significant inhibitory effect on the growth of carbon intensity. It is worth noting that the urbanization rate also has a significant inhibitory effect on carbon intensity. Therefore, the economic development in high electrification areas is becoming more mature, and the energy structure transition process is fast. On the premise of maintaining stable economic growth, the requirements to continue to optimize the energy consumption structure and reduce carbon emissions are particularly important in these areas. Specifically, the government should establish incentives for carbon reduction behaviors in the daily lives of residents to establish a low-carbon, green, and environmentally-friendly consumption concept and lifestyle concept; in addition, it should deepen the transformation of the energy structure and optimize the energy consumption structure according to the national development strategy. At the same time, we should learn from the international experience of cities with a relatively high electrification rate to achieve low-carbon development and a green economy.

(2) In regard to the areas with a medium electrification rate, the empirical results show that energy intensity and urbanization rate have a significant role in promoting carbon intensity, and energy consumption structure has a restraining effect on the growth of carbon intensity. It shows that the region is still in a “high-input, high-consumption, high-pollution” economic growth model, which is unsustainable. Therefore, in addition to enhancing people's awareness of environmental protection and advocating green and low-carbon living, the industrial upgrading should take the core role to reduce the energy intensity. At the same time, in the process of urbanization, we should promote low-carbon green methods to achieve high-quality economic and urban development.

(3) In regard to the areas with a low electrification rate, energy consumption structure and energy intensity have a significant role in promoting carbon intensity, while the impact of urbanization rate on carbon intensity is not significant. China's economic development has entered the mid-stage of industrialization. The rapid economic development and the heavy-duty characteristics of the economic structure have led to a strong increase in energy demand, which has brought great challenges to energy supply and environment. Optimizing energy consumption structure and improving energy efficiency have become key factors in coping with energy supply pressure. In low-electrification areas, increasing the level of electrification can effectively promote the improvement of energy efficiency. In combination with the characteristics of China's coal-based energy resources, the focus of optimizing the energy consumption structure should be to vigorously promote the conversion of coal to electricity, and to increase the power in the terminal energy In order to promote the improvement of

energy efficiency, reduce the total energy consumption and carbon intensity, and reduce environmental pollution.

(4) Overall, there are significant spatial differences in the impact of urbanization rate on carbon intensity in different regions. This is caused by unbalanced development in China, e.g., urban and rural development unbalances, regional development unbalances, structural unbalances, economic development and real economic development, and insufficient innovation capacity. Promoting a more balanced and comprehensive development can be carried out from three aspects: First, effective fiscal policy, through tax adjustments, should be established to encourage the industrial upgrading of enterprises in low- and medium-electrification regions, in order to transform the economic growth model, reduce carbon intensity, and reduce environmental pollution. The second is to carry out policy interventions in areas with low and medium electrification rates to support its economic development and energy structure transformation. The third is to increase the electrification rate in areas with low electrification rates, vigorously promote the conversion of coal to electricity, and increase the proportion of electricity consumed in terminal energy, in order to promote energy efficiency and reduce carbon intensity.

(5) It could be useful to incorporate the improvement of the level of electrification in the whole society into the national energy strategy, gather consensus on electrification development of all parties, and clarify electrification development as an important path to promote energy consumption, environmental reform, and economic development. The government should guide the rational layout and coordinated development of various types

of clean power generation, improve the safe operation and smart level of the power system, increase the power replacement and energy efficiency improvement in the industrial, construction, and transportation fields, deepen the reform of the power system, and stimulate new momentum for electrification development To narrow the gap in electrification levels between different industries and regions. The truly electrified development with green, safe, efficient and intelligent content will promote China's energy production and consumption revolution, supports the coordinated development of the economy and society, promotes the continuous improvement of the ecological environment, and helps the people's quality of life continue to improve.

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Credit author statement

I have made substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data for the work.

And I have drafted the work or revised it critically for important intellectual content; And have approved the final version to be published; And agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

All persons who have made substantial contributions to the work reported in the manuscript, including those who provided editing and writing assistance but who are not authors, are named in the Acknowledgments section of the manuscript and have given their written permission to be named.

No conflict of interest exits in the submission of this manuscript, and manuscript is approved by all authors for publication. I would like to declare on behalf of my co-authors that the work described was original research that has not been published previously, and not under consideration for publication elsewhere, in whole or in part. All the authors listed have approved the manuscript that is enclosed.

Ethical Approval

My manuscript does not report on or involve the use of any animal or human data or tissue, Not applicable.

Consent to Participate

Not applicable.

Authors Contributions

As the instructor, Jingqi Sun provided guidance on research ideas and methods. Xiaohui Guo conducted main writing work and empirical research. Yuan Wang wrote some literature reviews and subsequent revisions. Jing Shi provided methodological guidance and improvement. Follow-up proofreading and modification were carried out on Yiquan Zhou. Shen Boyang's main job is to proofread and polish the English

Availability of data and materials

The data of province-level CO2 emissions are obtained from China Emission Accounts and Datasets. http://www.ceads.net/.And other data are collected from National Statistics Bureau. http://www.statas.gov.cn/.

Consent for publication

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