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
The main purpose of this article is to link the environment, economy, electricity, and society and put forward a new point of view. The current research mainly explores the relationship between the environment, economy, and society and lacks a discussion on electricity. Using a new research framework, this article examines the relationship between energy intensity, energy consumption structure, population density, urbanization rate, and carbon intensity based on relevant data from 2000 to 2017 in China. In the empirical research, according to the cluster analysis, China’s 30 provinces are divided into three regions according to the electrification rate standard. The cross-sectional dependence test method is used to verify the cross-sectional dependence of the data, and the second-generation panel unit root test method is used. Exploring the relationship between the variables, this article finally uses the convergence analysis method to explore the degree of influence of each variable on the carbon intensity. The empirical results show that there are both short-term effects and long-term relationships in various regions, and the influencing factors of each region are different. It further shows that the carbon intensity of the four panels shows convergence, β absolute convergence, and β conditional convergence, but the main influencing factors in different regions are different. Finally, based on the results of empirical research, policy recommendations for reducing carbon intensity in different regions are put forward.

Keywords Carbon intensity · Electrification rate · Heterogeneous panel analysis · Convergence analysis

Introduction

By 2020, China’s GDP will be converted into US$ 14.72 trillion, which is 70.3% of the US GDP, and its share in the world GDP has also increased to 17%. From 1978 to 2020, China’s gross domestic product (GDP) increased from 367.87 billion yuan in 1978 to 101.6 trillion yuan in 2020, an increase of 39.2 times in terms of comparable prices, with an average annual real growth rate of 9.2%, which is the fastest growth rate in the world during the same period.

However, global CO₂ is predominantly caused by the combustion of fossil fuels that drive economic growth as
The share of fossil fuel consumption stands roughly 80% of all energy-producing sources as of 2018 (International Energy Agency). In the past two decades, empirical research has identified multiple determinants of environmental quality. All except a few of these studies have warned us against the rising threat of global warming (Chishiti et al. 2021). There is now an academic consensus backed by empirics that the rising ratio of carbon emissions, among other determinants, poses a potent threat to the environment. (Adedoyin et al., 2020; Malik et al., 2016).

In 2015, the Chinese government issued “Strengthening Climate Change Action – China’s National Independent Contribution,” promising to achieve the peak of carbon dioxide emissions around 2030. In 2020, General Secretary Xi Jinping announced to the whole world at the general debate of the 75th UN General Assembly that China decided to “strive to achieve carbon neutrality by 2060, thus forming China’s double carbon goal.” The “double carbon goal” is a major strategic decision made by China based on the internal requirements of promoting the construction of a Community of Shared Future for Mankind and realizing sustainable development. It is also China’s determination to actively respond to climate change and take a green and low-carbon development path. Chinese government undertakes to implement the carbon intensity reduction of 60–65% below 2005 level by 2030 (UNFCCC, 2015) in Intended Nationally Determined Contributions (INDCs). In the 13th Five-Year Plan (2016–2020), China formulates the mitigation targets of China (Cao Y et al., 2019).}

Many foreign scholars have begun to conduct research on carbon emission intensity. This research began in 1997. Rebiots J T and Grimes P E 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 and Grimes 1997). Zhang X offered useful insight into the nexus between income, electricity generation, and environmental pollution and applied a unique approach by deriving a theoretical and empirical model to examine the nexus between hydroelectric generation, renewable electricity generation, and CO2 (Zhang et al. 2021). In China, many scholars also reveal that the decline of carbon intensity during 2007–2012, such as Tan et al. (2011), who explained the 29.14% decline of carbon intensity in 1998–2008, and Su and Ang (2017), who revealed the CI decline at 26% in 2007–2012. The decreasing trend of carbon intensity slows down. Carbon intensity reduction will be a binding force in the long-term plan for national economic and social development (Cao Y et al., 2019).

In terms of panel data methods, Wang and Zhang used the 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 and Wei 2017). Based on the statistical data of 30 provinces, municipalities, and autonomous regions in China from 2004 to 2016, Feng, Zhang, and Wang used the 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 geographically 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 (Lin et al. 2018). Given the significant discrepancies of carbon intensity across provinces, sectors, and demand categories, the study is an attempt to integrate temporal with spatial decomposition to clarify the driving forces of carbon intensity from multiple levels and propose differentiated policies (Cao Y 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 carbon intensity and conducted empirical research on 281 prefecture-level cities in China from 2006 to 2016 (Zhang et al. 2020).
that China’s terminal electrification will reach 50% or even higher in 2050. However, in the current research, the relationship between electrification and carbon intensity is still unclear. Based on this background, 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, using heterogeneous panel technology to study the relationship between energy intensity, carbon intensity, energy consumption structure, urbanization rate, and population density in different regions is helpful to formulate corresponding carbon emission-reduction policies according to regional development characteristics.

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 cleaner, 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, and the power-centric energy transformation and upgrading is being accelerated. Therefore, the classification of 30 provinces in China based on the electrification rate is proposed to study the relationship between China’s electricity, economy, energy, and environment.

(2) 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, β 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 the “Literature review” section, the related literature review is introduced. In the “Proposed model, data, and descriptive statistics” section, data resource, descriptive statistics of variables, and the model adopted in this paper are presented. In the “Econometric methodologies” section, the major econometric methodologies are proposed. In the “Empirical findings and interpretations” section, the empirical findings and the interpretations of results are informed. In the “Conclusions and policy implications” section, the conclusions are summarized and some related policy remarks are proposed.

**Literature review**

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 USA. They conducted the first empirical study on the relationship between environmental quality and per capita income and put forward the EKC hypothesis (Grossman and Kruger 1991). Soumyananda D explained that 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 (Dinda 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 2000). Azomahou and Van Phu used nonparametric research methods, showing that the relationship between carbon dioxide emissions and GDP is more complicated than the EKC curve (Azomahou and Van Phu 2001).

However, more and more scholars have found that dual empirical models have 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 CO₂ emissions from a variety of perspectives. Ma XJ and others aim to quantify the relationship between real GDP, CO₂ emissions, renewable and nonrenewable energy consumption, tourism development, and labor force for France and Germany. Results reveal an inverted-U-shaped relation between CO₂ emissions and real GDP in the long run, confirming the validity of the environmental Kuznets curve for the group of France and Germany (Ma 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).

With the development of the economy, the factors affecting carbon emissions have become more extensive. Therefore, many scholars have analyzed the more specific factors affecting the carbon emission intensity.

In terms of energy 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 and Zhen 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 in carbon emissions in Sichuan Province from 2000 to 2011 through the LMDI model (Gao 2014). 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 the economic structure and external energy structure are positive-driving factors (Dong et al. 2019).

By coordinating the progress of electrification on the power supply side, power consumption side, and sustainable development level, we 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 et al. 2021), this leads to deviations in traditional panel analysis techniques based on homogeneous panel data. Therefore, the heterogeneous panel analysis method should be used.

In addition, urbanization is an important factor in regard to the relationship between GDP and CO₂ emissions. For example, Wang Z investigates the dynamic interdependence between CO₂ emissions, real gross domestic product (GDP), renewable and nonrenewable energy generation, urbanization, and export quality for both the top ten renewable energy and top ten economic complexity index (ECI) countries (Wang 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 between carbon dioxide and urbanization. This suggests that rapid urbanization 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).

Wang S found that in cities with low-carbon emission intensity, economic growth, technological progress, and appropriate population density play an important role in reducing emissions (Wang and Yongyuan 2019). Li H suggested that an increase in electricity consumption, population, and gross domestic product significantly contributed to enhancements in CO₂ emissions (Li et al. 2021).

From the above researches, it can be found that the two-way causal relationship between economy and environment has been made clear, and energy intensity and energy consumption structure are the internal driving factors of carbon intensity. In terms of social factors, population density and urbanization rate have an important impact on the environment. By coordinating the electrification process of the power supply side, power consumption side, and sustainable development level, we can promote the revolution of energy production and consumption, support the coordinated development of the economy and society, and promote the ecological environment. That is to say, these factors have complex influences on carbon intensity from different dimensions. However, the existing studies often explore the correlation from the time dimension. Moreover, the distribution of resources in China is quite different, and the degree of social development is not balanced. Therefore, we should combine the space and time dimensions to explore the correlation among electricity, economy, energy, and environment. Therefore, based on the regional differences, this paper mainly classifies the electrification rates of 30 provinces and studies the relationship among energy intensity, energy consumption structure, urbanization rate, population density, and carbon intensity in order to seek energy-saving and emission-reduction policies.

In summary, carbon emission from energy consumption is an inevitable by-product of economic development, especially those areas with large populations and high density have more carbon emissions, 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, the urbanization rate has also become a potential factor affecting carbon emissions. Therefore, based on the regional diversity, this article mainly studies the relationship among electricity, economy, energy, and the environment, by classifying 30 provinces by the electrification rate for energy-saving emission-reduction policies.

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 are 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.
Proposed model, data, and descriptive statistics

Proposed model and data

As suggested by previous studies (Wang and Yongyuan 2019, Abdeen Mustafa Omer 2007), urbanization, energy factors, and economic growth have significant effects on CO₂ 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).

\[
CI_{at} = f(U_{R,at}, ECS_{at}, PD_{at}, EI_{at})
\]  

(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., \( \text{CO}_2 \) emission per unit of GDP. \( UR \) is the urbanization rate counted by the proportion of the 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 total population. \( PD, ECS \) and \( EI \) are percentage-typed variables, their coefficient can stand for the elasticity directly. According to previous related researches (Zhu et al. 2017; Lotfalipour et al. 2010; Arouri et al. 2012), the logarithmic linear function is constructed as bellow:

\[
CI_{at} = \beta_{1a} UR_{at} + \beta_{2a} ECS_{at} + \beta_{3a} PD_{at} + \beta_{4a} EI_{at} + u_{ab}
\]  

(2)

where \( \beta_{1a}, \beta_{2a}, \beta_{3a}, \beta_{4a} \) are elasticities of \( CI \) with pertaining to \( UR, ECS, LPD, \) and \( EI \) per province, respectively. \( u_{ab} \) is the error with a mean of 0 and a variance of \( \sigma^2 \).

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 (HB), Jiangsu (JS), Jilin (JL), Shaanxi (SX1), Liaoning (LN), Ningxia (NX), Hunan (HN), Guangdong (GD), Hainan (HN), Qinghai (QH), Hebei (HB), Henan (HN), Xinjiang (XJ), Zhejiang (ZJ), Heilongjiang (HLJ), Jiangxi (JX), Sichuan (SC), Anhui (AH), Guangxi (GX), Shanxi(SX2), Guizhou(GZ), Yunnan (YN), Gansu (GS), and 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.

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.

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.

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.

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.

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.

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.

Fig. 3 The plane trend graph of CI

Fig. 4 The three-dimensional trend graph of ECS
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, China’s unbalanced development is caused by inadequate development, especially unbalanced urban and rural development, regional development, structural imbalance, economic development, inadequate development of the real economy, and inadequate innovation capabilities. As a result, all variables have inter-provincial differences,
which meet the requirements of quantitative 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.

In Table 3, by referring to the $P$-value, $<1\%$ presents the correlations among the analyzed variables for the national level, which indicates that CI has significant positive correlations with ECS and EI and has 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 low energy efficiency is harmful to urbanization. And coal consumption is still a significant element promoting GDP and UR.
Fig. 11 The plane trend graph of UR

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

| Objects | Variables | Mean | Median | Max. | Min. | Std. dev. | Skewness | Kurtosis |
|---------|-----------|------|--------|------|------|-----------|----------|----------|
| CI      | 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 |
Table 3 Correlations for the panel data set (p-values in parentheses)

| Correlation probability | CI     | LPD    | EI     | ECS    | UR     |
|-------------------------|--------|--------|--------|--------|--------|
| CI                      | 1.0000 | -0.358878 (0.0000) *** | 1.0000 | -0.436085 (0.0000) *** | 1.0000 |
| LPD                     | 0.909450 (0.0000) *** | -0.210544 (0.0000) *** | 0.366141 (0.0000) *** | 1.0000 |
| EI                      | 0.499894 (0.0000) *** | -0.511260 (0.0000) *** | -0.463933 (0.0000) *** | 1.0000 |
| ECS                     | 0.415491 (0.0000) *** | 0.506431 (0.0000) *** | -0.197431 (0.0000) *** | 1.0000 |
| UR                      | -0.415299 (0.0000) *** | 0.506431 (0.0000) *** | -0.511260 (0.0000) *** | 1.0000 |

***Statistical significance at 1% level

Econometric methodologies

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 the rise of central plains area. Thus, it is important to verify whether a cross-sectional correlation exists before the empirical analysis. According to existing studies (Pesaran 2007a, De Hoyos et al. 2006), this paper assumes that the standard represents the model:

\[ Y_{at} = \alpha_a + \beta_a X_{at} + \mu_{at}, \quad a = 1, 2, \ldots, A, \quad t = 1, 2, \ldots, T \]  

\[ \alpha \neq 1, 2, \ldots, T \]  

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

\[ \rho_{ad} = \frac{\sum_{t=1}^{T} \mu_{at} \mu_{dt}}{\sqrt{\sum_{t=1}^{T} \mu_{at}^2 \sum_{t=1}^{T} \mu_{dt}^2}} \]  

\[ CD = \sqrt{\frac{2T}{A(A-1) \sum_{a=1}^{A-1} \sum_{d=a+1}^{A} \rho_{ad}}} \rightarrow N(0, 1) \]  

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 et al. 2002; Breitung 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 2007b; Bhattacharyya et al. 2016). Thus, the cross-section Im-Pesaran-Shin (CIPS) method developed by Pesaran (Pesaran 2004) is adopted, using average individual statistics as follows:

\[ \Delta z_{at} = \alpha_a + \beta^*_a z_{at-1} + c_0 y_{t-1} + c_1 \Delta z_{a-1} + \mu_{at} \]  

where \( \Delta z_{at} = N^{-1} \sum_{n=1}^{N} z_{at} \) and \( \Delta \) represents the difference operator. Considering the serial correlation in the data, the model can be extended as follows:

\[ \Delta z_{at} = \alpha_a + \beta^*_a z_{at-1} + c_0 y_{t-1} + \sum_{k=0}^{r} \beta^*_k \Delta z_{at-k} + \sum_{k=1}^{K} \delta^*_k \Delta y_{at-k} + \mu_{at} \]  

where \( r \) is the lagged order determined by AIC and SIC. For each \( a \), the extended CADF regression is performed according to Eq. (7), and then the t-statistic of \( \beta^*_1 \) is obtained.

\[ CIPS = A^{-1} \sum_{a=1}^{A} \text{CADF}_a \]  

Convergence analysis method

William J (1988) pioneered the research on the convergence of economic growth, and then the convergence method was applied to the field of carbon emissions by Mark C (2003), and it was found that carbon emissions have convergence, but some scholars believed that the convergence of carbon emissions is country-specific (Van 2005). After many studies by scholars at home and abroad, convergence can be divided into three categories: \( \alpha \) convergence, \( \beta \) absolute convergence, and \( \beta \) conditional convergence; their mechanisms are as follows.

\( \alpha \) convergence

\( \alpha \) convergence test is a description of stock level, which reflects the dynamic process of regional carbon intensity deviating from the overall average level and its imbalance. In this paper, the compiler coefficient method in the \( \alpha \) convergence model is used to evaluate the development trend of the absolute gap of \( \chi \alpha \rho \beta \nu \) emission efficiency in regions with different electrification rates in selected 30 provinces.
The purpose of \( \beta \) 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 toward a good trend. The \( \beta \) absolute convergence model is shown below.

\[
\Delta CI_i = \alpha + \beta CI_{i,t-1} + \mu_{i,t}
\]

(11)

where \( CI_{i,t} \) indicates the carbon emission intensity at a certain electrification rate level in a certain year. \( \Delta CI_i \) indicates the difference between the carbon emission intensity at the electrification rate level of \( t+1 \) and \( t \) years. \( \alpha \) is a constant term. \( \mu_{i,t} \) is an error term. When \( \beta < 0 \), the results pass the significance test; it is proved that there is the “catch-up effect.” If there is a “catch-up effect,” it means that the carbon emission intensity situation at the electrification rate level of \( t+1 \) and \( t \) years. \( \alpha \) is a constant term. \( \mu_{i,t} \) is an error term. \( \chi_i \) is the control variable.

### Empirical findings and interpretations

#### Cross-sectional dependence test

The results of the cross-sectional dependence test are 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 10%, which indicates that the cross-sectional dependence exists. Therefore, the second generation of panel unit root detection technology is introduced.

According to the results of Breitung (Breitung and Pesaran 2009), in panel data model analysis, if there is cross-section correlation, it will cause correlation or cross-section heterogeneity among disturbance items, which will affect the first-order and second-order properties of standard panel data estimators, such as unbiasedness and validity, as well as other related properties of statistics in model analysis. At the same time, Yang Z found that although the first-generation panel unit root test made use of cross-section dimension information and significantly improved its test efficiency (Yang et al. 2015), however, if the first-generation method is used to analyze the cross-section unit without paying attention to the significant correlation, it may lead to significant deviation in conclusion (Yang et al. 2015). In view of

| 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** |

*** Rejection of null hypothesis at 1% significance level
** Rejection of null hypothesis at 5% significance level
* Rejection of null hypothesis at 10% significance level

\( \Delta CI_i = \alpha + \beta CI_{i,t-1} + \mu_{i,t} \)
this, many scholars have put forward the second-generation panel unit root test method one after another. They consider heterogeneous components by introducing heterogeneous impacts into multiple unobservable factor models or using single-factor structure so as to conduct unit root test under the panel framework and overcome the cross-section-related problems, in reality, thus greatly enhancing the conclusion (Phillips and Sul 2003; Pesaran 2007a).

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, 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 are presented in Table 5, indicating that all variables are unstable at the level and the first difference. In most foreign studies, all the variables are nonstationary at level; however, after taking the first difference, all the series become stationary, implying that there are cointegration and long-term relationships among all variables (Ahmad et al. 2020; Zhang et al. 2021).

As shown in Table 5, in each panel data, the stationarity of all variables in level and the first difference are random, which may be due to the large differences in environment, economy, policy, power development level, and speed in different places, the short-term effects and long-term correlations among the variables. For example, in the HERR region, EI has a short-term effect on carbon intensity, which is because the economic development of the HERR region tends to mature and the process of energy structure transformation is fast, so the impact on carbon intensity can be revealed quickly. In the LERR area, EI has a short-term effect on carbon intensity. However, due to the low electrification rate, backward energy-saving, and emission-reduction technologies, it consumes more energy, and at the same time, the local economy is generally backward, so it has an obvious short-term effect on carbon intensity. Similarly, in the LERR area, the urbanization rate is generally low, so it is difficult to popularize energy-saving and emission-reduction technologies, and the energy consumption is large, which will have obvious short-term effects with carbon intensity.

### Table 5 Panel unit-roots results

| Region | CIPS test | Variable | CI | LPD | EI | ECS | UR |
|--------|-----------|----------|----|-----|----|-----|----|
| 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 | −2.2 | −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 |

CIPS test is estimated applying constant and trend with 1 lag
***Rejection of null hypothesis at 1% level of significance
**Rejection of null hypothesis at 5% level of significance
*Rejection of null hypothesis at 10% level of significance

### Table 6 Standard deviation under Nation, HERR, MERR, and 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 | 2.710734 | 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 | 2.123259 |
| 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 |
Convergence analysis results

$\alpha$ convergence results

In this paper, the carbon intensity from 2000 to 2017 has been tested for $\alpha$ convergence, and the standard deviation of each year is shown in Table 6 at the level of Nation, HERR, MERR, and LERR:

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 Fig. 12.

As shown in Fig. 12, the overall trend of each region is a downward trend; that is, the carbon intensity shows an $\alpha$ convergence trend, which approaches their respective steady-state levels.

In the whole country, the overall trend of carbon intensity deviation is declining, showing a convergence trend, which indicates that the electrification development in the whole country is more balanced and fuller, and the electrification level of the whole society is continuously improved. The electrification process will more effectively promote the green and low-carbon transformation of energy and power development and provide strong support for the high-quality development of China’s economy and society.

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 rates and relatively stable economic growth. The process of energy structure transformation is relatively fast, and the energy consumption structure is relatively optimized. Therefore, the fluctuation degree of carbon intensity is small. In areas with low electrification rates, the energy structure is still dominated by coal and electricity, the energy structure transformation is intensified, and the economic growth is also fast, so the volatility of carbon intensity is relatively high.

The overall fluctuation degree of each region has a downward trend, but the carbon emission intensity increased obviously in 2003 and also increased slightly in 2016 compared with the previous year.

Xu G thinks that the trends of carbon emissions per capita in the east, the middle, and the west are different and have their own changing rules (Xu 2010). Tang J also divided the region according to geographical location and found that carbon intensity converged in part-time and diverged in other time periods (Tang and Shuyan 2014). However, Yang X’s study found that the regional differences between provinces in China’s agricultural carbon intensity are getting bigger and bigger as time goes by, and there is no convergence characteristic (Yang et al. 2015). Compared with the literature on geographical regionalization, the regionalization by electrification rate method in this paper can better reflect the correlation between carbon intensity and electrification rate. As shown in Fig. 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.

**β absolute convergence results**

As can be seen from Table 7, coefficients 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 that there is a “catch-up effect” in the carbon intensity under the horizontal panel of each electrification rate, the carbon intensity is absolutely convergent.

In some earlier documents of dividing regions by geographical location (Xu 2010; Tang and Shuyan 2014; Yang et al. 2015), it is generally believed that there is no β absolute convergence in different regions because regional differences increase the difficulty of reaching agreement on energy-saving policies in different regions and reduce the possibility of reaching consensus on the choice of energy-saving policies, and the difference in carbon intensity in the whole country will not be automatically eliminated. The latest research generally believes that there is absolute β convergence in carbon intensity and carbon emission in different regions (Lin et al. 2018; Zhang et al. 2021; Guo et al. 2021). This is mainly due to the country’s vigorous strengthening of environmental regulations on energy conservation and emission reduction after the Twelfth Five-Year Plan, which has achieved remarkable results. The development of the whole country is more balanced, and the gaps in the environment, technology, electricity, and economy are gradually reduced, so the phenomenon of the “catch-up effect” finally appears.

**β conditional convergence results**

It can be seen from Table 8 that in the results of β conditional convergence regression, β < 0 and passed the significance test, that is, in areas with different electrification rates, the carbon intensity approaches their steady-state levels. In the heterogeneous panel, 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 have positive effects on the growth of CI, among which EI plays a more significant role, while UR and ECS have significant inhibitory effects on the growth of carbon intensity. In HERR and MERR, EI plays the most significant role in promoting the growth of CI, followed by UR. In LERR, energy consumption structure and energy intensity have a significant role in promoting the growth of carbon intensity, but LPD has an inhibitory effect on the growth of CI. The main reason is that, in HERR, the more advanced technology of energy conservation and emission reduction, which improves the energy utilization rate, thus reducing energy consumption and restraining the CI.

In addition, there are significant spatial differences in the impact of UR on CI in different regions. It can obviously inhibit the carbon intensity in HERR, promote the growth of CI in MERR, and has no significant effect on CI in LERR. The reason is that, under the non-synchronous level, in HERR, with the increase of UR, the energy structure transformation is deepening, and efforts are made to increase the consumption proportion of clean energy such as non-fossil energy and natural gas, scientifically and rationally develop coal power, oil and gas, nuclear power, hydropower, and renewable energy, speed up the construction of modern energy system, implement dual control of total energy consumption and intensity, and steadily improve the green and low-carbon level of the whole society, so the energy consumption is high in electrification rate. However, the traditional economic development mode characterized by “three highs and one low,” that is, the economic growth mode of high-input, high-consumption, high-pollution, low efficiency has brought serious negative impacts on the environment and ecology. The energy structure in the areas with medium electrification rate is still dominated by coal, and

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**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 |
| 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 |
| 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 |
| 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: 0.4735, 0.6486, 0.8198, 0.511888
the second energy mode dominated by oil and gas has not yet been completed, and the third energy revolution represented by the change of energy utilization mode is also facing (Stan 2018). Under this background, UR has a significant role in promoting CI.

Related studies also show obvious timeliness. Some literatures think that different regions divided by geographical locations do not exist or partially exist β conditional convergence (Xu 2010; Tang and Shuyan 2014; Yang et al. 2015), and some recent literature believe that there is β conditional convergence in all regions (Xianzhao et al. 2018; Zirui 2021; Guo et al. 2021).

This shows that dividing regions by electrification rate is more conducive to studying the influencing factors of carbon intensity. In addition, China has successively issued low-carbon policies such as the Notice of Comprehensive Work Plan for Energy Conservation and Emission Reduction in the Twelfth Five-Year Plan and the Interim Measures for the Management of Carbon Emission Rights Trading, which have made important efforts for the environment and achieved remarkable results.

Conclusions and policy implications

The main purpose of this article is to investigate the relationship between energy intensity, energy consumption structure, population density, urbanization rate, and carbon intensity based on relevant data from 2000 to 2017 in China. In the empirical study, because of the heterogeneity of my country’s carbon intensity, according to the cluster analysis, China’s 30 provinces are divided into three regions according to the electrification rate standard. If there is a cross-sectional correlation, it will cause the correlation or cross-sectional heterogeneity between the disturbance items, which will affect the order attributes of the first-order and second-order standard panel data estimators, such as unbiasedness and validity. Using the cross-sectional dependence test method proposed by Pesaran M et al., it is found that there is cross-sectional dependence. The second-generation panel unit root test method can effectively overcome the cross-sectional dependence problem. The results show that energy intensity, energy consumption structure, population density, and urban are short-term effects and long-term relationships coexisting in the conversion rate and carbon intensity, so the convergence analysis method is used to explore the degree of influence of each variable on carbon intensity. The empirical results show that the influencing factors of different regions are different. From an overall point of view, energy consumption structure and population density have a greater impact on carbon intensity.

Based on these findings, this academic work has some important policy implications.

First of all, the research results show that a series of low-carbon policies adopted by the government have begun to show initial results. The carbon intensity has been significantly reduced, and it has also shown a positive effect on economic and social development. Although the gap between regions is decreasing year by year, the gap still cannot be ignored and more targeted recommendations should be implemented in different regions. Therefore, we should actively respond to and implement the “3060” plan. For areas with high electrification rates, the daily carbon reduction behaviors of residents and individuals are encouraged to establish a low-carbon saving, green, and environmentally friendly consumption concept and life philosophy. In addition, according to the national development strategy, the energy structure transformation is deepened and the energy consumption structure is optimized. For areas with a high-input, high-consumption, low-pollution, low-efficiency electrification rate, in addition to enhancing people’s awareness of environmental protection and advocating a green and low-carbon life, industrial upgrading should be the core role, the economic structure should be optimized, innovation-driven models should be realized, and energy intensity should be reduced. In low electrification areas, optimizing the energy consumption structure and improving energy efficiency have become key factors in coping with the pressure of energy supply. It is necessary to vigorously promote the conversion of coal to electricity and increase the proportion of electricity in the final energy consumption to promote the improvement of energy efficiency, thereby reducing the total energy consumption and carbon intensity, reducing the environmental pollution.

Secondly, combining all the panel data, there are significant spatial differences in the impact of urbanization rate on carbon intensity in different regions. This is caused by the inadequate development of my country, especially the unbalanced urban and rural development, regional development, and structure; sexual imbalance; inadequate economic development; inadequate development of the real economy; and inadequate innovation capabilities. Promoting a more balanced and full development can be carried out from three aspects: first, effective fiscal policies, through tax adjustments, to encourage industrial upgrading in some areas with low and medium electrification rates, transform economic growth models, 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 their 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 consumption in the final energy. In this way, it promotes the improvement of energy efficiency and reduces carbon intensity.
Third, include improving the level of electrification of the whole society into the national energy strategy, consolidating the consensus of all parties on the development of electrification, and clarifying the development of electrification as an important path to promote energy consumption, environmental reform, and economic development. The government should guide the rational distribution and coordinated development of various types of clean power generation energy, improve the safe operation and intelligent level of the power system, increase the power substitution and energy efficiency improvement in the industry, construction, and transportation fields, deepen the reform of the power system, and stimulate new momentum for the development of electrification, to narrow the gap in electrification levels between different industries and regions. The development of electrification, which is truly green, safe, efficient, and intelligent, promotes China’s energy production and consumption revolution, supports coordinated economic and social development, promotes the continuous improvement of the ecological environment, and promotes the continuous improvement of people’s quality of life.

Finally, the study found that dividing different regions by electrification rate for heterogeneous panel analysis is more conducive to studying the influencing factors of carbon intensity than dividing regions by geographic location, which provides a new thinking direction for future research.

There are some limitations in this research, which provides the possibility for future research. First of all, this research only focuses on China, and future research can use different regions and countries to test the framework proposed here. Secondly, the variables considered in this article are limited, and there are many emerging factors that affect carbon intensity, such as the development of intelligent technology. Future research should pay more attention to the development of society in order to obtain unique insights.

**Availability of data and materials** The data of province-level CO2 emissions are obtained from China Emission Accounts and Datasets, [http://www.ceads.net/](http://www.ceads.net/), and other data are collected from National Statistics Bureau, [http://www.stats.gov.cn/](http://www.stats.gov.cn/).

**Authors contribution** 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 by Yiquan Zhou. Shen Boyang’s main job is to proofread and polish the English.

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**Declarations**

**Ethics 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.

**Consent for publication** Not applicable.

**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.

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**References**

Omer AM (2007) Focus on low carbon technologies: the positive solution, 12(9):2331-2357

Fatia AF, Adewale AA, Victor BF (2020) An assessment of environmental sustainability corridor: the role of economic expansion and research and development in EU countries.[J]. The Science of the total environment,713

Kasman A (2015) Yavuz Selman Duman. CO2 emissions, economic growth, energy consumption, trade and urbanization in new EU member and candidate countries: a panel data analysis. Economic Modelling. 4:97–103

Manzoor A, Zeeshan K, Ur RZ, Iqbal KS, Ullah KZ (2021) Can innovation shocks determine CO2 emissions (CO2E) in the OECD economies? A new perspective[J]. Economics of Innovation and New Technology, 30(1):1-12

Khalid AM, Muhammad U, Iqbal GD, Shahzad SM, Arshian S, Iqbal TM, Baes LL (2021) Does globalization affect the green economy and environment? The relationship between energy consumption, carbon dioxide emissions, and economic growth. [J]. Environmental science and pollution research international. York, Richard. Demographic trends and energy consumption in European Union Nations, 1960–2025. Social science research, 2007, 36(3): 855-872

Arouri MEH, Youssef AB, M’henni H, Rault C (2012) Energy consumption, economic growth and CO2 emissions in the Middle East and North African countries. Energy Policy 45:342–349

Saravanan AP, Pugazhendhi A, Mathimani T (2020) A comprehensive assessment of biofuel policies in the BRICS nations: implementation, blending target and gaps[J]. Fuel, 272

Saravanan AP, Mathimani T, Deviram G, Rajendran K, Pugazhendhi A (2018) Biofuel policy in India: a review of policy barriers in sustainable marketing of biofuel[J]. Journal of Cleaner Production, 193
Dinda S (2004) Environmental Kuznets curve hypothesis: a survey[J]. Ecological Economics, 49(4)
Stan (2018) The characteristics of the new round of energy revolution and the institutional mechanism construction of energy transformation [J]. Financial think tank, 2018(04):17-25 139-140
Wang S, Wei Z (2017) Analysis of the carbon intensity factors of Beijing-Tianjin-Hebei based on the whole-region-industry decomposition. Soft Science 31(12):96–100
Wang S, Yongyuan H (2019) Spatial spillover effect and driving factors of carbon emission intensity of Chinese cities. Acta Geographica Sinica 74(06):1131–1148
Wang Z, Mehdij BJ, Mara M, Buhari D, Umer S (2021) Does export product quality and renewable energy induce carbon dioxide emissions: evidence from leading complex and renewable energy economies? [J]. Renewable Energy 171
Baumol WJ, Wolff EN (1988) Productivity growth, convergence, and welfare: reply[J]. The American Economic Review, 78(5)
Yong X, Bin Q, Ziwen C, Liang H, Sheng S (2020) Detection methods of illegal wireless communication links in power Internet of Things terminals [J]. Journal of Electrical Technology 35(11):2319–2327
Zhang X, Jiang Q, Khattak SI, Ahmad M, Rahman ZU (2021) Achieving sustainability and energy efficiency goals: assessing the impact of hydroelectric and renewable electricity generation on carbon dioxide emission in China[J]. Energy Policy, 155
Xu G (2010) carbon emission convergence: theoretical hypothesis and empirical study of China [J]. Research on quantitative economy, technology and economy, 2010,27(09):31-42
Yingjie Y, Gelui S, Yadong L, Xiuming D, Wang H, Xiuchen J (2016) Transformer state anomaly detection based on sliding window and clustering algorithm [J]. High Voltage Technology 42(12):4020–4025
Xiuyu Y (2016) analysis of regional differences and convergence of agricultural carbon emissions in China [J]. Hubei agricultural sciences, 2016,55(04):1066-1072.
Yang Z, Shuoja K, Yongliang Z (2015) Comparative study on the properties of limited samples of the second generation panel unit root test method [J]. Quantitative Economic and Technical Economic Research 32(12):124–141
Chuanguo Z, Lin Y (2012) Panel estimation for urbanization, energy consumption and CO2 emissions: a regional analysis in China. Energy Policy 49:488–498
Zhu L, Zhen Z (2011) Analysis of influencing factors of carbon emission intensity in Shanghai. Environmental Science Research, 2011, 24 (1): 20 – 26
Zhu Z, Yang L, Tian X, Wang Y, Zhang Y (2017) CO2 emissions from the industrialization and urbanization processes in the manufacturing center Tianjin in China. Journal of Cleaner Production 8:67–75
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