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Original Research

An Emerging Force for Curbing Carbon Emissions: Convergence of Digital and Energy Industries

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Abstract

The digital industry and the energy industry are the two primary forces behind contemporary economic and social progress, and their convergence development is the necessary path to realizing carbon peak and carbon neutrality goals. The paper measures the level of convergence of the digital industry and energy industry (CDIEI) and empirically examines its relationship with China's 30 provinces' carbon emissions (CE) between 2012-2021. Considering the differences in geographical location and industrial convergence level, the heterogeneity of the CDIEI on CE was analyzed. The intrinsic influence mechanism and nonlinear effects of the two were deeply explored. The results indicated that the CDIEI can reduce CE, which was further corroborated by several robustness checks. The carbon reduction effect of the CDIEI is more significant in the central and eastern regions, as well as in high convergence areas. The CDIEI can curb CE by stimulating industrial structure upgrading (ISU) and boosting green technology innovation (GTI). When ISU and GTI cross a single threshold, the CDIEI can significantly curb CE. The study's findings offer reference value for raising the CDIEI and minimizing CE immediately.

Keywords: digital industry and energy industry, industrial convergence, carbon emissions, industrial structure upgrading, green technology innovation

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Introduction

Background and Motivation

In this day and age, climate change has grown to be a significant worry. Empirical evidence overwhelmingly confirms that carbon emissions (CE) are the primary cause of climate change [1]. The IEA reported that global energy-related CE reached a new high of over 36.8 billion tons in 2022. Energy consumption and CE have grown rapidly over the past 40 years in China. The economy's rapid advancement has resulted in a steady rise in CE [2], resulting in an annual CE of more than 6 billion tons [3]. According to the IEA's CO_2 Emissions in 2022 publication, China's CE was 11477 million tons in 2022. To address the climate challenge, the entire world has been called upon by the UN to take immediate action [4]. Nearly 200 nations worldwide, including China, signed the *Paris Agreement* in 2015. Reducing CE has become a major concern for society [5], and it has also become a global issue related to the sustainable development of the world economy [6]. Against this background, we need to explore a low-carbon development path that suits our national conditions.

To enhance energy efficiency [7], accelerating industrial restructuring [8] is a recommended method for reducing CE. Industrial convergence can realize industrial structural adjustment and is an inevitable trend of industrial system modernization [9]. It requires the mutual interpenetration and extension of knowledge, application, technology, and other aspects among different industries [10] and a new industrial form. Currently, the convergence of the digital and energy industries (CDIEI), has gained the attention of researchers [11]. The digital industry itself, as a new strategic industry, can achieve green development. With the CDIEI a role for the digital industry in the energy field is becoming increasingly prominent. Firstly, the digital industry can directly participate in the low-carbon process of energy, thereby reducing CE. Secondly, it can improve energy utilization efficiency and reduce energy consumption. Thirdly, it can also optimize the energy structure, reduce energy pollution, and improve environmental quality. The energy industry can also provide high-quality energy security for the development of the digital industry. The deep CDIEI is a trend, and the convergence of the two helps the energy industry gradually exhibit green, digital, and intelligent attributes. Achieving low-carbon goals is the core goal of the CDIEI. Meanwhile, the NEA pointed out the need to strengthen the construction of new infrastructure that converges traditional energy and digital intelligent technology, unleashes the potential for value in energy data elements, and provides strong support for actively and steadily promoting carbon peak and carbon neutrality. This requires promoting the CDIEI. Therefore, modern industrial systems must be constructed, and the industrial development model must be modified in order to lower CE. Promoting the CDIEI is an inevitable choice for China to fulfill its low-carbon targets.

Literature Review

Research on Industrial Convergence

Convergence is the process by which technological services and industrial structures evolve [12]. It occurs when innovation takes place at the intersection of established industries with clear boundaries. The resulting technologies and products generate new applications within their respective industries [13]. The convergence between industries is the gradual weakening of industry borders, and the convergence with other industrial functions helps create new industries that weren't previously available, in addition to helping to restructure the industrial structure [14]. There are two categories into which the literature on industrial convergence can be subdivided. The first category is research on the CDIEI, Wang et al. [11] used principal component analysis to calculate the degree of convergence between China's overall and regional digital and energy industries from 2002 to 2018 and, based on this, studied the influencing factors of the convergence development of the two industries. The results indicate that the convergence level of China's digital and energy industries is on the rise. Chen et al. [15] used the entropy weight method to measure the development level of China's energy industry and digital economy and used a coupled coordination model to measure the degree of energy digitization. Through the use of methods like kernel density analysis, the changing features of China's energy digitization were examined. The results showed that the current energy digitization is in a barely coordinated state. The second category is research on the convergence of other industries. Dong et al. [16] used a spatial econometric model to investigate the effect of China's manufacturing and productive services convergence on green development efficiency. The two have a positive relationship with each other. Cao et al. [10] looked at how different stages of industrial convergence affected China's metabolic efficiency and found that while industrial convergence generally has a positive influence on metabolism, its driving force changes depending on the level at which it occurs. Zhou et al. [17] analyzed how China's digital and automobile industries were convergent. The automotive and digital industries in China are tightly connected, with 2018 being an important turning point for the two industries from disjointed to coordinated. Dong et al. [9] empirically investigated how China's 2001-2014 convergence in the information industry had an impact on the manufacturing sector's high-quality development, and it was discovered that industrial convergence helped the sector's increase in energy efficiency. Technological innovation can indirectly improve energy efficiency through industrial convergence.

In terms of measuring industrial convergence, the following four approaches are commonly used in the existing literature: the Herfindahl index, patent coefficient, input-output method, and coupling coordination model [18]. Among these methods, given that the coupled coordination degree model can represent the degree to which many systems are developing synergistically and are more suitable for measuring the level of CDIEI, this model is used in this paper.

Research on the Influencing Factors of Carbon Emissions

Factors such as economic development level, urbanization, opening up level, environmental regulation intensity, and human capital level will have an impact on CE. Grossman and Krueger [19] analyzed the relationship between economic development and CE and found a "U-shaped" relationship, namely the environmental Kuznets curve. Some scholars also believe that the relationship between the two is an "inverted N-shaped" relationship [20]. Some studies suggest that after the Industrial Revolution, the growth of the world economy led to a rapid increase in CE [21]. The relationship between urbanization and CE is relatively complex. Tang et al. [22] argue that with the rapid advancement of urbanization, a large amount of energy consumption and CE are rapidly increasing. On the contrary, Adams and Nsiah [23] argue that urbanization can improve carbon emission efficiency, improve management levels, and promote technological progress, thereby reducing CE. The opening up level to the outside world also has an impact on carbon emissions. Shen et al. [24] argue that while opening up to the outside world brings benefits to enterprises, it may also lead to excessive resource utilization, resulting in an increase in CE. Similarly, imports are also affected. Salman et al. [25] point out that with the increase in imported products, the consumption of transportation will also increase, so CE will further increase. The series of environmental protection policies introduced by our country have, to some extent, affected CE. Zhang et al. [26] argue that environmental regulations will not reduce CE, which is known as the "green paradox". Wu et al. [27] argue that although environmental regulation can promote CE in western China, it can reduce CE in other regions. There is a close relationship between the human capital level and the environment. Bano et al. [28] argue that, in the long run, human capital will improve CE. However, Çakar et al. [29] argue that human capital only suppresses CE at low growth levels and vice versa at high growth levels.

Research on the Impact of Industrial Convergence on Carbon Emissions

It was discovered through a review of relevant research that there are two categories of studies on the connection between industrial convergence and CE. The first category is research on the impact of the CDIEI on CE, which is relatively rare. Wang et al. [11] used principal component analysis to calculate the convergence level of the digital and energy industries in China as a whole and in various regions from 2002 to 2018. The study found that the convergence of the digital and energy industries helps to advance the fulfillment of the "dual carbon" goal. The second category is research on the impact of the convergence of other industries on CE. Lin and Heng [30] studied the relationship between the level of convergence in the development of manufacturing and productive service industries and carbon emission efficiency in 30 provinces of China from 2003 to 2017. The results showed that the convergence of the two industries can significantly improve carbon emission efficiency. Kuan and Lei [31] used mediation models and spatial Durbin models to study the impact of rural industrial convergence on agricultural CE in 30 provinces and cities in China from 2008 to 2020. The results showed that rural industrial convergence can suppress carbon CE by optimizing labor, expanding land scale management, and promoting agricultural technological progress. Bangsheng et al. [32] used a bidirectional fixed effects model to calculate the impact of rural primary, secondary, and tertiary industry convergence on agricultural CE in 30 provinces and cities in China from 2011 to 2020. The study showed that rural industry convergence can suppress agricultural CE. Xia et al. [33] used a three-stage least squares method to analyze the impact of the convergence of China's manufacturing and digital services industries on CE from 2006 to 2018 and concluded that there is a "U-shaped" relationship between the two.

Through a review of relevant literature, it was found that there are currently shortcomings in the research for the CDIEI on CE:

(1) Lack of research on the CDIEI.

(2) The existing literature on the digital industry, energy industry, and CE mainly focuses on the relationship between the two. Currently, there are no articles that incorporate the CDIEI and CE into a unified research framework.

(3) The existing literature lacks empirical analysis ideas on the CDIEI on CE.

This study takes the following steps to address the above deficiencies or gaps:

(1) Construct an indicator system for the digital industry and energy industry, using the entropy approach and coupling coordination degree model to calculate the CDIEI level. Use an ArcGIS visual map to analyze the trend of the level of CDIEI. The work adds to the existing literature on measuring industrial convergence.

(2) Incorporated the CDIEI and CE into the same research framework and analyzed the impact of the CDIEI on CE.

(3) The article empirically tests the impact of the CDIEI on CE and innovatively, according to the level of industrial convergence, by dividing China's 30 provinces

into high convergence regions and low convergence regions to examine how differing regional convergence levels affect CE. Selecting two variables, ISU and GTI, as mechanism variables and threshold variables, we explore the impact mechanism and nonlinear effects of the CDIEI on CE.

Here are the remaining sections of the article: Section 2 presents the theoretical analysis and proposes the research hypotheses. Section 3 describes the research design of the article. Section 4 conducts the empirical analysis and gives the results. Section 5 contains conclusions and policy recommendations. Fig. 1 depicts the specific framework for this article.

Theoretical Analysis and Research Hypotheses

The Impact of the Convergence of the Digital Industry and the Energy Industry on Carbon Emissions

With the development of society, the digital industry and the energy industry are infiltrating each other. CDIEI is an effective resource convergence method that can reduce operating costs. It allows limited resources to be used for research and development of new products to improve energy efficiency [34]. It can also promote a comprehensive and interconnected upgrading and transformation of related industries, reducing the consumption of fossil energy and improving production energy efficiency [35], thereby achieving carbon reduction. Meanwhile, the CDIEI can have a profound impact on the entire energy system. If energy pollution happens, quick action can be taken to stop it from worsening, thus curbing CE [36].

Hypothesis 1. The CDIEI can curb CE.

The Impact Mechanism of the Convergence of the Digital Industry and the Energy Industry on Carbon Emissions

The CDIEI can effectively promote the ISU because industrial convergence helps promote innovation in conventional industries, which in turn encourages the industrial structure to be optimized. The digital industry and energy industry have moved from gradual interpenetration to full convergence, which is conducive to the realization of ISU and facilitates its development in the direction of rationalization, high-end modernization, and greening [37]. Industrial restructuring is an effective way to curb CE [38]. ISU may modify the structure of energy-intensive industries by allocating production elements logically, thus realizing the purpose of reducing CE [39]. Therefore, relocating beyond the secondary into the third sector of the economy can be conducive to curbing CE [40].

Dong et al. [16] believed that industrial convergence could promote GTI. GTI is an innovation mode coordinated with the ecological environment [41]. The digital industry is environmentally friendly, so the deep CDIEI might enhance resource use in an efficient manner and capital allocation, release the vitality of green innovation, reduce energy consumption and pollution emissions, and then stimulate enterprises

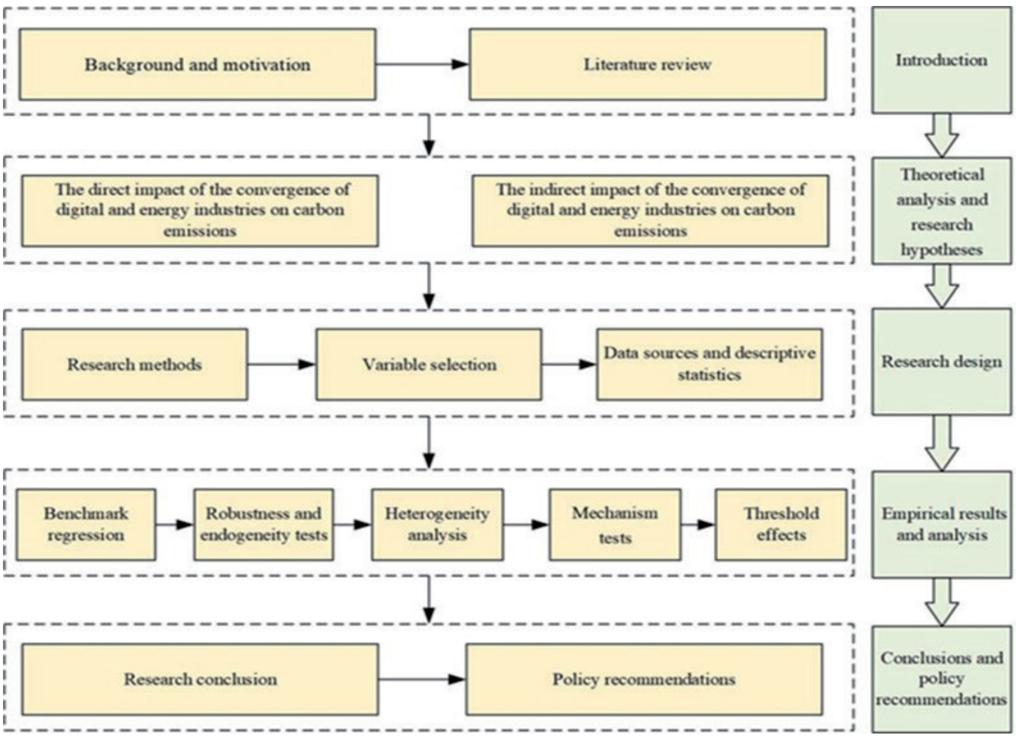

Fig. 1. Full-text framework diagram.

to undertake green innovation research, protect the environment, save energy and reduce emissions, and promote regional GTI. GTI is an important means of reducing CE [33]. GTI can not only significantly reduce CE but also meet the goal of ecological protection [42]. It can reduce CE by reducing energy intensity, improving production efficiency, and enhancing the environment's condition [43].

Hypothesis 2. The CDIEI can curb CE by promoting ISU and enhancing GTI.

The Nonlinear Impact of the Convergence of the Digital Industry and the Energy Industry on Carbon Emissions

The ISU will lead to a phased change in CE. In the initial period, China's secondary industry had a very unsteady basis and was driven by scientific and technological innovation and social demand. The rise of secondary industry and its dominance over a country's industrial structure have led to the rapid growth of China's economy. It has resulted in a sharp increase in energy consumption [44]. Consequently, when the industry grows more intense, the importance of the tertiary industry also increases. It is essential for adjusting the industrial structure, but it also greatly encourages conserving energy and the reduction of emissions [45]. It is an important force for reducing carbon, reducing pollution, and expanding green. So, the ISU will have a jump in the impact on CE.

The inhibitory effect of GTI on CE shows an increasing trend. Initially, the application of GTI is in a period of experimentation and demonstration. When the promotion of green ideas has only just begun, green technological innovations are not a good impediment to CE reductions; when the application of GTI reaches a certain phase, technology, machinery configuration, and management will be improved. The green platform has been improved, the green concept has been widely recognized, the distribution of resources is more sensible, the upgrading of GTI has become faster, and CE has been curbed. Fig. 2 depicts the theoretical analysis of this research.

Hypothesis 3. The CDIEI has a non-linear impact on CE due to the ISU and the improvement of GTI.

Research Design

Research Methods

Kernel Density Estimation

The overall spatial differences and dynamic evolution trends of CE in the 30 provinces of China in 2012, 2015, 2018, and 2021 are depicted using the Kernel density estimate's nonparametric estimate to more intuitively represent the spatial distribution of China's CE. The formula is shown below:

$$f(x) = \frac{1}{N_h} \sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right) \tag{1}$$

Among them, N_h is the number of observation values. X_i represents the observation point value, x is the average value, h represents bandwidth, and $k(\cdot)$ represents the kernel functions. Select Gaussian kernel functions that have been widely used in existing research, as shown below:

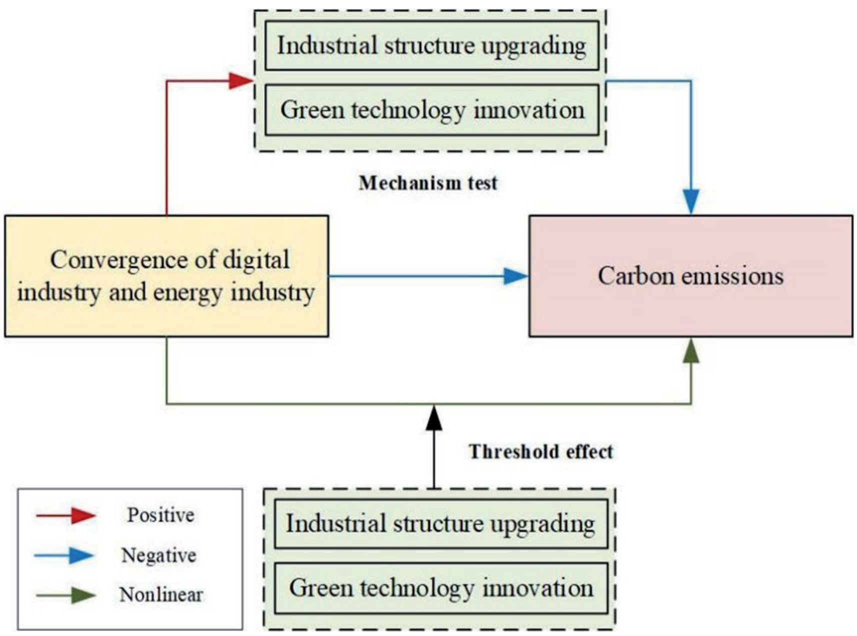

Fig. 2. Mechanism analysis of the CDIEI on CE.

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp(-\frac{x^2}{2}) \quad (2)$$

Entropy Method

Standardize the data and calculate the indicator weights.

Step 1, Standardization of indicators:

$$\text{Positive indicators: } x_{ij}' = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \quad (3)$$

$$\text{Negative indicators: } x_{ij}' = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \quad (4)$$

Among them, x_{ij}' reflects the standard value, x_{ij} represents the original value, provinces are denoted by *i*, $i = (1,2,\ldots,n)$, indicators are denoted by *j*, $j = (1,2\ldots,m)$.

Step 2, To eliminate the impact of "0" after standardization on subsequent calculation results, let $x_{ij} = x_{ij}+10^{-4}$. The following is the formula for calculating the proportion of indicator characteristics:

$$X_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}'} \quad (5)$$

Step 3, Calculate the information entropy of indicators:

$$e_j = -\frac{1}{\ln n} \sum_{j=1}^{n} (X_{ij} \times \ln X_{ij}), (0 \le e_j \le 1) \quad (6)$$

Step 4, Calculate the coefficient of difference g_i and indicator weight

$$g_j = 1 - e_j \quad (7)$$

$$w_j = \frac{g_j}{\sum_{j=1}^{m} g_j} \quad (8)$$

Coupling Coordination Degree Model

Construct a model for estimating the CDIEI level:

$$C = 2\left[\left(U_1 U_2\right) / \left(U_1 + U_2\right)^2\right]^{\frac{1}{2}} \quad (9)$$

$$CDIEI = \sqrt{C \times T} \qquad 0 \le CDIEI \le 1 \quad (10)$$

$$T = \alpha U_1 + \beta U_2 \quad (11)$$

Among them *C* is the degree of coordination between the digital industry and the energy industry in China, based on which the mutual relationship between the two can be determined; *U1* and *U2* represent the comprehensive indicator values of the two industries, respectively; *CDIEI* represents the level of convergence between the digital industry and the energy industry, which tends to be closer to 1, signifying a greater *CDIEI* level; *T* is the composite indicator's level of development for the two industries; α and β represent the undetermined weight coefficient, with $\alpha + \beta = 1$, considering that the two industries are equally important in this study; $\alpha = \beta = 0.5$.

Benchmark Regression

Constructing the following model for testing the connection between *CDIEI* and carbon emissions (*lnCE*):

$$lnCE_{it} = \alpha_0 + \alpha_1 CDIEI_{it} + \alpha_2 Control_{it} + \mu_i + v_t + \varepsilon_{it} \quad (12)$$

Among them, $lnCE_{it}$ is the carbon emissions of province *i* in year *t*, $CDIEI_{it}$ represents the convergence level of the digital industry and energy industry, $Control_{it}$ is the relevant control variables, μ_i and v_t are divided into fixed effects of province and time, while ε_{it} is a random error term.

Mechanism Tests

Drawing on the ideas of Ting [46], the following mechanism testing model is constructed:

$$med_{it} = \beta_0 + \beta_1 CDIEI_{it} + \beta_2 Control_{it} + \mu_i + v_t + \varepsilon_{it} \quad (13)$$

Among them, *med* represents mechanism variables and incorporates industrial structure upgrading (*STU*) and green technology innovation (*lnGTI*), while others are consistent with the above.

Threshold Models

Prior theoretical analysis shows that the influence of the CDIEI on CE may have nonlinear characteristics. Therefore, referring to Hansen [47], constructing panel threshold models:

$$lnCE_{it} = \sigma_0 + \sigma_1 CDIEI_{it} \times I(q_{it} \le \theta) + \sigma_2 CDIEI_{it} \times I(q_{it} > \theta) + \beta_3 Control_{it} + \mu_i + v_t + \varepsilon_{it} \quad (14)$$

Among them, q is the threshold variable, representing *STU* and *lnGTI*, respectively. θ is the corresponding threshold value, $I(\cdot)$ is the indicator function, which estimates a value of 0 in the absence of the condition in parenthesis and 1 when it is satisfied. The remaining variables are consistent with the above.

Variable Selection

Dependent Variable

Considering the IPCC [48] as a reference, calculate the 30 provinces' CE in China from 2012 to 2021 and take logarithmic values. CE mainly comes from the combustion of fossil fuels and industrial processes. In this article, fossil energy is subdivided into seven energy categories: coke, coal, diesel, kerosene, gasoline, fuel oil, and natural gas. In industry, the study only considers CE from cement production and estimates CE using the following expression:

$$lnCE = \sum_{k=1}^{7} E_k \times CEF_k + M_0 \times Q = E_k \times H_k \times CH_k \times COR_k \times \frac{44}{12} + M_0 \times Q \tag{15}$$

Among them, k is the fossil energy type, E_k is the k-th energy consumption, CEF_k is the emission coefficient during the combustion of k-type energy, M_0 is the CE coefficient in the process of making cement, and Q is the volume of cement produced. After further decomposition of the CE coefficient, H_k stands for the k-type energy's average low calorific value. CH_k denotes the carbon content per unit of calorific value during fossil fuel combustion, COR_k represents the carbon oxidation factor, and 44/12 represents the molecular weight proportion for carbon dioxide to carbon.

To explore the dynamic distribution characteristics of CE in various provinces of China, kernel density estimation was used to obtain CE kernel density plots for 30 provinces in China in 2012, 2015, 2018, and 2021, as shown in Fig. 3. Firstly, from a positional perspective, there has been no significant shift in the center of CE nuclear density since 2012. From the curve shape, it shows a single peak characteristic as a whole, with the peak in 2012 being the highest, followed by 2015, 2018, and 2021. The peaks have gradually shifted from the "sharp peak" to the "broad peak", indicating a significant spatial imbalance in China's CE. The differences in economic development, technological level, urbanization level, and other factors lead to differences in CE among different provinces. The kernel density estimation curve in 2021 exhibits a right "trailing" phenomenon, indicating an increase in the proportion of provinces in China with high CE in 2021. The improvement of independent research and innovation capabilities in various regions, coupled with limited technological capabilities for reducing CE, led to an increase in CE in some provinces. Therefore, investigating China's low-carbon development route is essential.

Independent Variable

Taking into account the evolution of China's digital industry and energy industry, taking full account of all factors, and based on a summary of existing studies, in keeping with the principles of scientificity, operability, representativeness, and data accessibility, three aspects have been taken into consideration when creating a system of indexes for the digital and energy industries: industrial scale, industrial structure, and industrial efficiency and includes a quantity of 16 secondary indicators. The *CDIEI* is measured using the coupling

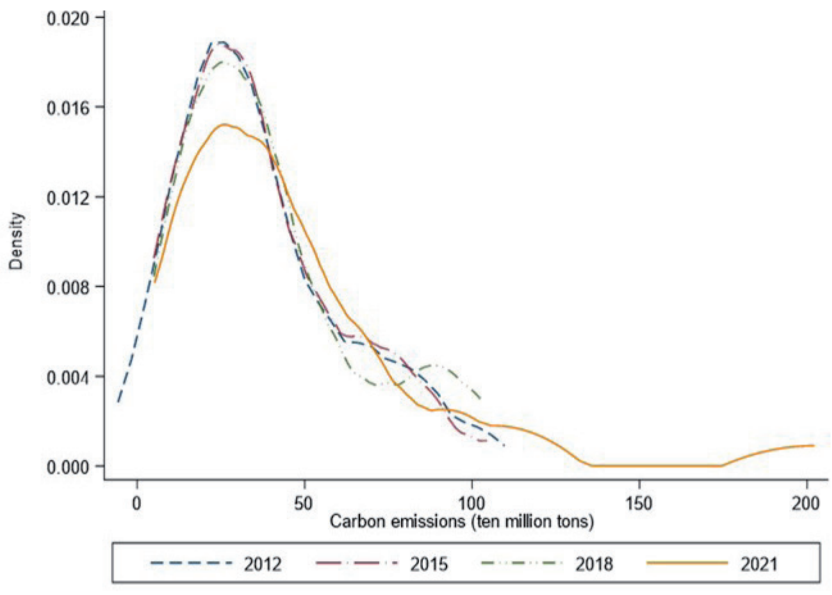

Fig. 3. CE kernel density plots of 30 provinces in China in 2012, 2015, 2018, and 2021.

coordination degree model. The specific indicator construction is detailed in Table 1.

To show the CDIEI and its spatial distribution characteristics features more graphically and intuitively, this paper selects the average annual convergence level of 30 provinces in China in 2012-2015, 2016-2018, and 2019-2021, and draws an ArcGIS visual map as shown in Fig. 4. First of all, from an overall perspective, from 2012 to 2021, the CDIEI in 30 provinces in China has shown different degrees of improvement but is still in the development stage; the eastern seaboard has greater levels of convergence, the middle region comes in second, the northwest region is last, and the level of CDIEI varies widely across provinces, with some cities far surpassing others. From 2012 to 2015, only Beijing, Jiangsu, and Guangdong provinces and cities had a good level of convergence; from 2016 to 2018, eight regions, Beijing, Shanghai, Shandong, Jiangsu, Zhejiang,

Table 1. Evaluation index system for the development level of the digital industry and energy industry.

	Primary Indicators	Secondary Indicators	Method of Calculation	Unit	Attribute
Digital Industry	Industrial Scale	Operating income from a computer, communication, and other electronic equipment manufacturing industries	-	ten thousand yuan	+
		Software business revenue	-	ten thousand yuan	+
		Total telecommunications business volume	-	ten thousand yuan	+
		Internet broadband access users	-	10,000 households	+
	Industrial Structure	The proportion of information transmission, software, and information technology services in urban employment	Employment of urban units in information transmission, software, and information technology services / Employment personnel in urban units×100%	%	+
		Number of high-tech industry enterprises	-	-	+
	Industrial Efficiency	Operating profit of computer, communication, and other electronic equipment manufacturing industry	-	ten thousand yuan	+
		The proportion of R&D expenditure to GDP	R&D expenditure / GDP	%	+
Energy Industry	Industrial Scale	Total energy consumption	–	10000 tons of standard coal	–
		Total primary energy production	–	10000 tons of standard coal	+
		Total electricity consumption	–	10000 kWh	–
	Industrial Structure	Coal consumption proportion	Total coal consumption/total energy consumption×100%	%	–
		The proportion of electricity consumption	Total electricity consumption/total energy consumption×100%	%	–
		Proportion of natural gas consumption	Total natural gas consumption/total energy consumption×100%	%	+
	Industrial Efficiency	Comprehensive energy consumption with an added value of 10000 yuan	Total energy consumption/industrial added value	Tons of standard coal /ten thousand yuan	–
		GDP energy intensity	Total Energy Consumption/GDP	Tons of standard coal / ten thousand yuan	–

Guangdong, Sichuan, and Shaanxi, had a better level of convergence. While the convergence level of Hubei, Anhui, Yunnan, and Guizhou showed a significant increase from 2019 to 2021, the convergence level of Hebei, Hunan, Jiangxi, Hainan, Gansu, and Xinjiang improved, while the convergence level of Qinghai and Ningxia was relatively low.

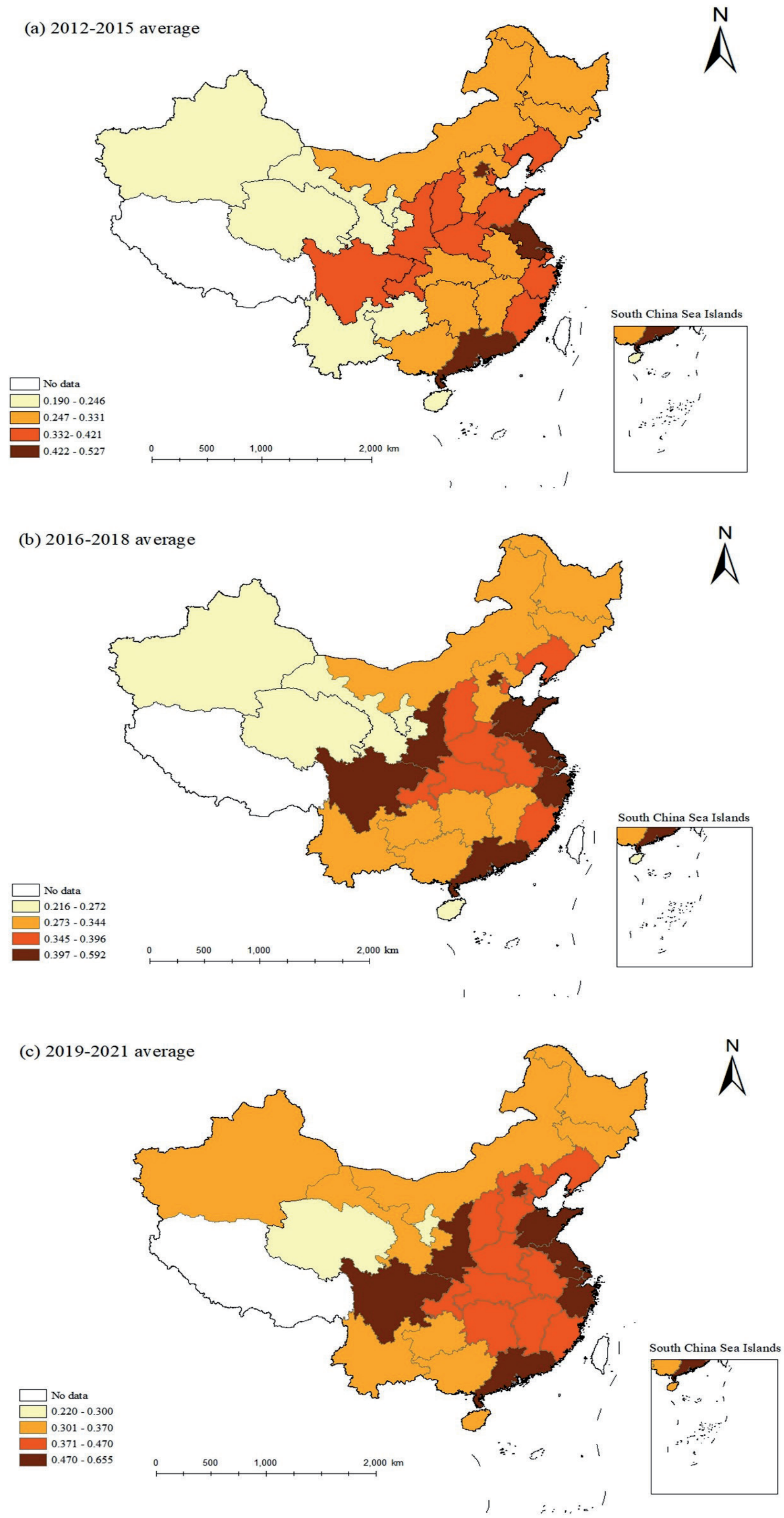

Fig. 4. ArcGIS visual map of the level of CDIEI from 2012 to 2021. Source: This map depends on a standard map that was acquired from the Standard Map Service website of the National Bureau of Surveying and Mapping Geographic Information. It has the review number GS (2022) 1873. There are no changes to the original map.

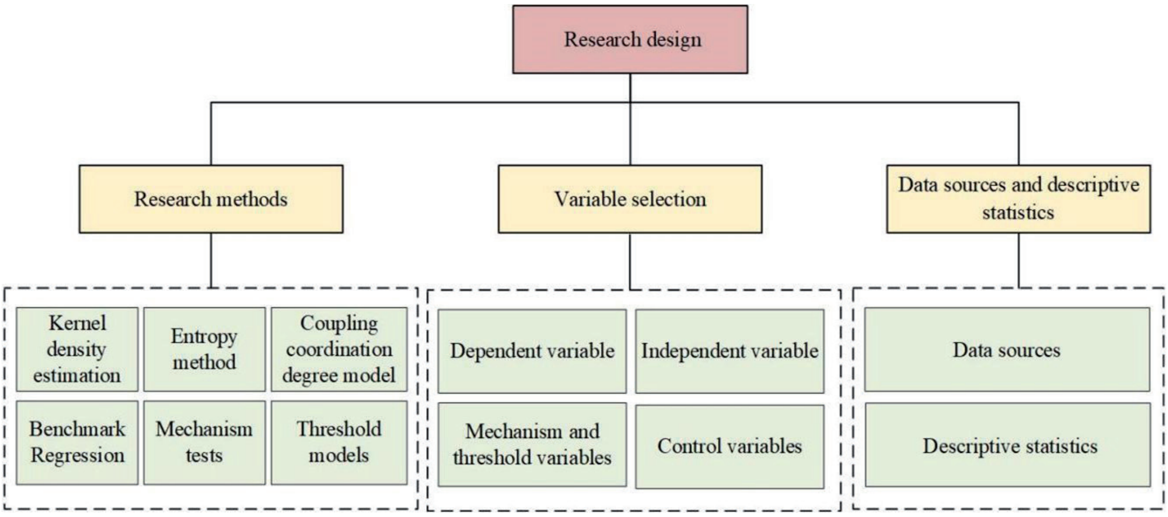

Fig. 5. Research design framework.

Mechanisms and Threshold Variables

The prior theoretical analysis demonstrates that *STU* and *lnGTI* are selected as mechanisms and threshold variables. The *STU* is represented by the tertiary industry's value-added divided by the secondary industry's value-added. *lnGTI* shows the total number of green patent applications and logarithmic.

Control Variables

Referencing existing literature, five variables that affect CE have been chosen as control variables: Economic development level (*lnGDP*), measured and logarithmized using per capita GDP; Urbanization (*URB*), expressed as the ratio of the resident urban population to the annual resident population of the region; Opening up level (*OPEN*), determined by the total amount of imports and exports relative to GDP; Environmental regulation intensity (*ER*), expressed as the ratio of completed investment in industrial pollution control to the value-added of industry; Human capital level (*HC*), expressed as the ratio of the number of students enrolled in higher education to the total local population.

Data Sources and Descriptive Statistics

Based on 30 provinces and cities in China, 2012-2021 (Hong Kong, Macao Special Administrative Region of China, Taiwan, and Tibet Autonomous Region are not covered due to missing data). 2012-2021 data is taken from the *China Statistical Yearbook*, the *China Energy Statistical Yearbook*, the *China Electronic Information Industry Statistical Yearbook*, the *China High Tech Industry Statistical Yearbook*, the *Regional Statistical Yearbook,* the National Bureau of Statistics, and CNRDS databases. Interpolation is used for partially missing data. Fig. 5 shows the research design.

The statistical status of the variables that were chosen for this paper can be seen in Table 2. The CDIEI is 0.365 on average, which shows that the level of CDIEI in China is still at a low level and requires improvement. In addition, its largest value is 0.681, while the smallest

Table 2. Descriptive statistics of variables.

Variables	Variable name	Obs.	Mean	Std. Dev	Min	Max
lnCE	Carbon emissions	300	10.320	0.751	8.415	12.220
CDIEI	Convergence of the digital industry and energy industry	300	0.365	0.101	0.176	0.681
STU	Industrial structure upgrading	300	1.283	0.710	0.549	5.297
lnGTI	Green technology innovation	300	7.562	1.336	3.738	10.380
lnGDP	Economic development level	300	9.325	0.464	8.598	10.780
URB	Urbanization	300	0.601	0.119	0.363	0.938
OPEN	Opening up level	300	25.900	27.730	0.757	144.100
ER	Environmental regulation intensity	300	0.003	0.004	0	0.031
HC	Human capital level	300	0.021	0.006	0.009	0.043

Table 3. The benchmark regression results.

Variables	(1)	(2)
CDIEI	-1.154**	-1.503***
	(-2.267)	(-2.793)
lnGDP		0.290***
		(2.839)
URB		1.130**
		(2.560)
OPEN		0.001
		(1.072)
ER		-13.704***
		(-4.855)
HC		-11.151*
		(-1.815)
Province FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.169	0.294
Obs.	300	300

Notes: T-statistics in parentheses; ***$p<0.01$, **$p<0.05$, *$p<0.1$; Capital FE means fixed effect.

is 0.176, representing a large gap in the CDIEI among China's provinces, consistent with the previous results.

Empirical Results and Analysis

Benchmark Regression

To test the CDIEI on CE, a benchmark regression is conducted on the full sample data. Before model testing, the Hausman test was first used to decide between a fixed effects model and a random effects model, which showed a p-value equal to 0.0000. The original hypothesis was rejected. For benchmark regression, a fixed effects model was thus selected. In Table 3, column (1) indicates the *CDIEI* effect *lnCE* without considering control variables. The regression result indicates that for every 1% rise in the *CDIEI*, *lnCE* will reduce by 1.154% and be significant at the 5% level. The effect of the *CDIEI* on *lnCE* after considering relevant control variables in column (2), indicates that when relevant factors work together, for every 1% increase in the *CDIEI, lnCE* will be reduced by 1.503%, which is significant at the 5% level. Therefore, the *CDIEI* can curb *lnCE*. With the continuous deepening of the CDIEI, the relationship between the digital industry and the energy industry has become increasingly close. The convergence of the two industries has improved energy production and utilization efficiency, ensured the quality of energy resources, and reduced environmental pollution related to energy. Hypothesis 1 is established.

In the control variables, *lnGDP* and *lnCE* are significantly positive at the 1% level. Economic growth will be accompanied by resource consumption and energy use, leading to an increase in *lnCE*. *URB* and *lnCE* are significantly positive at the 5% level. *URB* promotes energy consumption, traffic congestion, and urban population aggregation, which in turn, exacerbates environmental pollution and *lnCE*. The regression coefficient between the *OPEN* and *lnCE* is positive but not significant. The *OPEN* at this time cannot significantly affect *lnCE*. *ER* and *lnCE* are significantly negative at the 1% level, despite the remarkable success of *ER* in China, generally reducing *lnCE*. *HC* and *lnCE* are significantly positive at the 10% level. *HC* helps to absorb foreign technology, providing technical support for saving production and reducing *lnCE*.

Robustness and Endogeneity Tests

Robustness Tests

As noticed in Table 4, to guarantee the study's robustness, the paper examines three aspects. Firstly, the dependent variables are switched to per capita carbon emissions (*lnPCE*) for a fixed effects regression. In column (1), the *CDIEI* is still significant at the 5% level. Secondly, four municipalities were excluded from the data. Given that China's municipalities have a higher degree of economic development than the country as a whole and the increasing emphasis on environmental protection, also an important pillar of China's development, there is a certain gap between them and the national average, and the regression results will have an impact. In column (2), the *CDIEI* is still significant at the 5% level. Third, the shrinking of independent variables. In order to avoid adverse effects of abnormal values, non-random measurement results, and non-randomness measures, In column (3), the independent variable is re-estimated after shrinking the upper and lower 1%. The above three robustness tests indicate that the coefficient sizes and significance levels of the independent variables change slightly. There has been no obvious shift in the coefficients' significance or sign. Therefore, the benchmark regression results have strong robustness and credibility, so the CDIEI can curb CE.

Endogeneity Tests

The above robustness test has, to some extent, alleviated the endogeneity issues that may exist in this study, but it still cannot avoid errors. To address these issues, the lagged 1-period term of the *CDIEI* was used as the instrumental variable (IV) for 2SLS regression. Table 4 column (4) shows that the results of the first stage test are significantly positive, and the Cragg Donald Wald F-value is 814.30, which is greater than the critical value of 10, rejecting the null hypothesis of weak instrumental variables and indicating that the

Table 4. Robustness and endogeneity tests.

Variables	Replace the dependent variable	Excluding municipalities	Independent variable tail reduction processing	Instrumental variable	
	(1) *lnPCE*	(2) *lnCE*	(3) *lnCE*	First stage (4) *CDIEI*	Second stage (5) *lnCE*
IV				0.340***	
				(3.690)	
CDIEI	-1.174**	-1.558**	-1.649***		-6.569**
	(-2.200)	(-2.512)	(-2.993)		(-2.079)
Control	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
F	-	-	-	814.30	-
R^2	0.180	0.348	0.298	0.992	0.979
Obs.	300	260	300	270	270

Notes: T-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1; Capital FE means fixed effect.

constructed instrumental variables are reasonable. The results of the second stage of column (5) indicate that the regression results are consistent with the benchmark regression results, indicating that there are no endogeneity issues caused by omitted variables or reverse causality, further confirming the credibility of the benchmark regression results.

Heterogeneity Analysis

Heterogeneity Analysis of Geographical Location

China's different regions differ greatly in terms of their degree of development, and there is significant regional heterogeneity in *lnCE*. Table 5 also proves that the *CDIEI* to curb *lnCE* is indeed influenced by geographical location. Referring to the approach of Xiaobo et al. [49], it divides the 30 provinces of China into eastern, middle, and western. In columns (1) and (2), the *CDIEI* in the eastern and middle regions is significant at the 5% level, representing that the *CDIEI* in the eastern and middle regions can curb *lnCE*. In the western region, the coefficient is negative but not significant. Representing the *CDIEI* has no significant impact on *lnCE*. The root cause of this result is that the middle and eastern regions of China have developed economies, can provide sufficient funds, and have a lot of high-quality and high-level talents, advanced technology, and a broad market. These provide a good basis for the *CDIEI*, which is conducive to curbing *lnCE*. Although the western region has abundant energy resources, high-tech industry development continues to be comparatively slow, economic development is backward, and the level of science, technology, and

Table 5. Heterogeneous regression results.

Variables	Geographical location			Industrial convergence level	
	(1) Eastern	(2) Middle	(3) Western	(4) High convergence regions	(5) Low convergence regions
CDIEI	-0.667*	-3.491**	-0.703	-0.850*	1.320**
	(-1.953)	(-2.576)	(-1.026)	(-1.873)	(2.017)
Control	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.388	0.322	0.475	0.209	0.238
Obs.	110	80	110	150	150

Notes: T-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1; Capital FE means fixed effect.

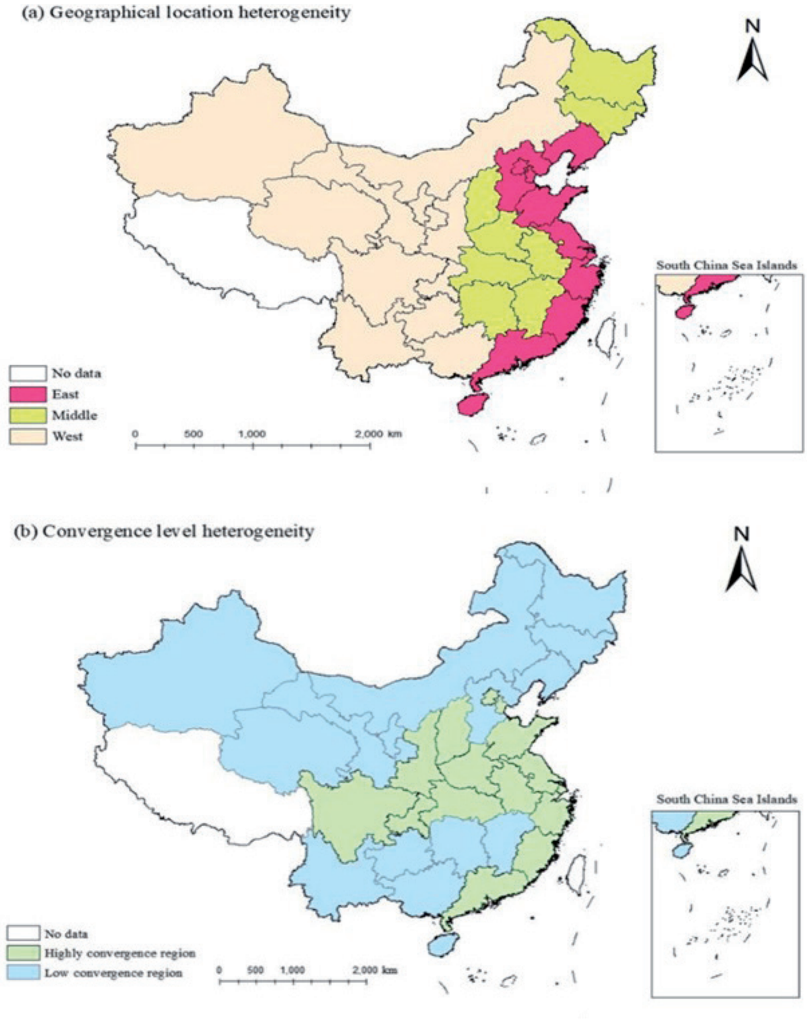

Fig. 6. Geographical location and industrial convergence level distribution map.
Source: This map depends on a standard map that was acquired from the Standard Map Service website of the National Bureau of Surveying and Mapping Geographic Information. It has the review number GS (2022) 1873. There are no changes to the original map.

education lags, resulting in insufficient demand for industrial convergence and an inability to effectively curb *lnCE*.

Heterogeneity Analysis of Industrial Convergence Levels

Both the digital industry and the energy industry that has developed differ greatly throughout China's provinces, resulting in different levels of industry convergence. Based on this, using the average level of *CDIEI* as a benchmark for group regression of 0.37, regions above the average are called high convergence regions, below the average are called low convergence regions. In Table 5, columns (4) and (5), the *CDIEI* in high convergence regions will increase by 1% and *lnCE* decrease by 0.85%, significant at the 10% level; a rise with the *CDIEI* of 1% in low convergence regions will increase *lnCE* by 1.32% and is significant at the 5% level. This can represent that high convergence regions have better enjoyed the dividends of industrial convergence, and greater *CDIEI* levels imply a larger contribution to *lnCE*; in low convergence regions, due to the lack of infrastructure, technology, and talent support, the development of the digital industry and energy

Table 6. Mechanism test results.

Variables	(1) *STU*	(2) *lnGTI*
CDIEI	1.575**	2.828**
	(2.105)	(2.324)
Control	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.820	0.820
Obs.	300	300

Notes: T-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1; Capital FE means fixed effect.

Table 7. Threshold effect results.

Threshold variables	Threshold type	F	P	Critical value			Threshold value	95% Confidence intervals
				10%	5%	1%		
STU	single	22.55	0.067	19.410	25.021	34.920	1.296	(1.263, 1.303)
lnGTI	single	31.51	0.017	19.488	22.673	33.742	5.660	(5.498, 5.759)

industry is unbalanced, which restricts the convergence development of the two industries and exacerbates the development gap between regions. The distribution of geographical location and industrial convergence level is shown in Fig. 6.

Mechanism Tests

Mechanism Testing of Industrial Structure Upgrading

Table 6's column (1) results indicate that the *CDIEI*'s impact coefficient on *ISU* is 1.575 at the 5% level, which is significant. The *CDIEI* influences the *ISU* positively, as it helps to share resources between industries, improve resource utilization efficiency, reduce resource

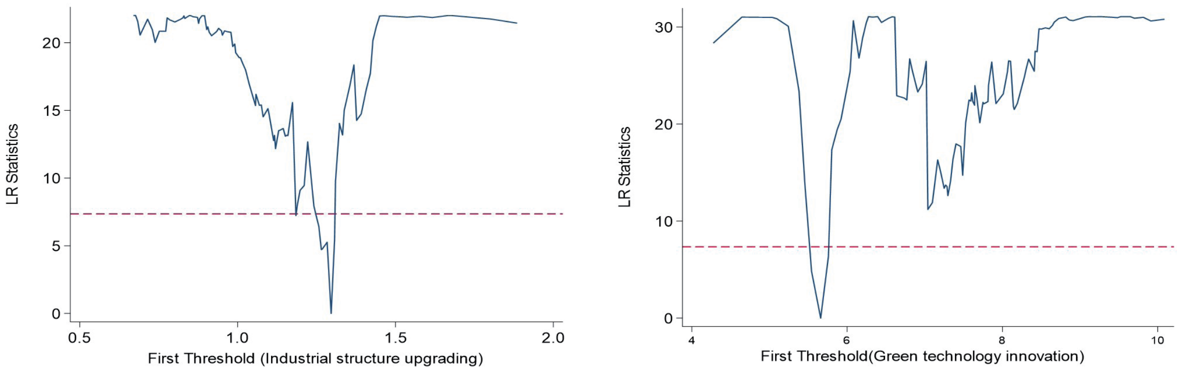

Fig. 7. Single threshold model threshold parameters.

Table 8. Panel threshold regression model estimation results.

Threshold variables	(1) *STU*		(2) *lnGTI*	
CDIEI × *I* (*ISU*≤1.296)	0.176			
	(0.473)			
CDIEI × *I* (*ISU*>1.296)		-0.056**		
		(-1.986)		
CDIEI × *I* (*lnGTI*≤5.660)			-1.300***	
			(-3.961)	
CDIEI × *I* (*lnGTI* >5.660)				-1.502*
				(-2.682)
Control	Yes		Yes	
Province FE	Yes		Yes	
Year FE	Yes		Yes	
R-squared	0.255		0.232	
Obs.	300		300	

Notes: T-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1; Capital FE means fixed effect.

waste, improve resource quality and efficiency, and promote the *ISU*. The above results indicate that promoting *ISU* is an important channel for the *CDIEI* to curb *lnCE*, consistent with theoretical analysis.

Mechanism Testing of Green Technology Innovation

Table 6's column (2) results indicate that the *CDIEI*'s impact coefficient on *GTI* is 2.828 at the 5% level, which is significant. The *CDIEI* influences the *GTI* positively because it can accurately allocate factor resources, reduce high pollution production links, minimize environmental emissions and energy use, lower costs of technological innovation, and increase its capacity and efficiency, thus laying the foundation for improving *lnGTI*. Therefore, the *CDIEI* can curb *lnCE* by enhancing the *lnGTI*. The above results indicate that upgrading *lnGTI* is an important channel for the *CDIEI* to curb *lnCE*, consistent with theoretical analysis. Hypothesis 2 is established.

Threshold Effects

Based on this previous theoretical research, it is clear with the *ISU* and the improvement of the level of *lnGTI*. The *CDIEI* will have a nonlinear effect on *lnCE*. Therefore, the test is conducted using a panel threshold model. Table 7 contains the threshold effect test and the threshold value estimation. The results of 300 bootstrap simulations indicate that there is a single threshold value for both *ISU* and *lnGTI*. The threshold value for *ISU* is 1.296, and the threshold value for *lnGTI* is 5.660.

To verify the authenticity of the existence of threshold values, construct likelihood ratio function graphs for the two threshold variables mentioned above. When the resulting threshold value lies within the LR value of the confidence interval, it means that the threshold value is true. From Fig. 7, single threshold values for *ISU* and *lnGTI* are both within the 95% confidence interval, so the model passes the test.

After passing the test, the regression analysis was performed using the panel threshold model and parameter estimates in Table 8.

The Threshold Effect of Industrial Structure Upgrading

The effect of the *CDIEI* on *lnCE* is positive but not significant when the *ISU* is less than the threshold value of 1.296. When the *ISU* crosses the 1.296 threshold, the effect of the *CDIEI* on *lnCE* is significantly negative. It indicated that China may have underdeveloped tertiary industries at the initial stage of *ISU*, mainly labor-intensive manufacturing, and the proportion of industry is relatively large, with significant differences in industrial structure across regions, leading to the promotion of *lnCE* through *ISU*. However, as the level of *ISU* increases, the *CDIEI* is beginning to gradually reduce *lnCE*, which indirectly indicates that the reduction effect of the *CDIEI* on *lnCE* depends on the *ISU*.

The Threshold Effect of Green Technology Innovation

When *lnGTI* is less than the threshold value of 5.660, the *CDIEI* has a significant and reducing effect on *lnCE*; when *lnGTI* crosses the threshold of 5.660, the *CDIEI* has a more significant reduction effect on *lnCE*, reaching 1.502 and significant. Indicating that *lnGTI* can improve the ecological environment while maximizing economic and social benefits. Therefore, enhancing the level of *lnGTI* can significantly improve environmental quality and reduce *lnCE*. Therefore, Hypothesis 3 is established.

Conclusions and Policy Recommendations

This article explores the impact of CDIEI on CE based on panel data from 30 provinces in China from 2012 to 2021. The findings indicate that the CDIEI level is generally showing varying degrees of improvement but is still in a developmental stage. The CDIEI is beneficial for curbing CE. After several robustness tests and endogeneity discussions, the finding is still true. Heterogeneity analysis shows that CDIEI in the eastern and middle regions and high convergence regions can curb CE. The CDIEI can also reduce CE by promoting ISU and enhancing GTI, and there is a non-linear effect when crossing a single threshold. The role of CDIEI in curbing CE will be strengthened. Given this, the following policy recommendations are proposed:

First, comprehensively and actively promote the development of the CDIEI. There is still significant room for improvement in CDIEI in China, as well as the potential for CE reduction. We need to accelerate the exploration of new industry models and realize a greater leap forward between the industries. Improving the infrastructure construction of the digital and energy industries, creating a digital energy open cooperation park, and adhering to the idea of low-carbon and environmentally friendly growth will strengthen open cooperation in the digital energy industry, promote domestic and foreign dual circulation coordination, promote the CDIEI, and curb CE.

Secondly, based on one's reality, explore industry convergence models that are suitable for the local area according to local conditions. Correctly understand the development gap between provinces, continue to optimize the convergence model of the digital industry and energy industry in the eastern and middle regions, reduce CE, and promote local green development. The CDIEI in the western region urgently needs to be improved. We need to strengthen the foundation of the digital industry and energy industry, actively propel the CDIEI, and improve support policies for the western region. Low convergence regions need to strengthen their connections with high convergence regions, learn from their experiences, systematically formulate development strategies for the CDIEI, and promote coordinated regional development.

Thirdly, attach importance to the important role played by ISU and GTI. ISU and GTI are important paths for the CDIEI to reduce CE. The government needs to identify and judge whether the existing industrial structure is coordinated and reasonable, screen out factors that hinder the rationalization of industrial structure, promote ISU, and correspondingly relax regulations to provide a relaxed macro environment for industrial convergence. Increase financial support for GTI, promote GTI for enterprises, concentrate on creating, introducing, and promoting green technology, and further achieve green and low-carbon development in industrial convergence.

The CDIEI is key to reducing CE. Our series of empirical tests supports the results and provides new ideas for reducing CE. However, further work still needs to be done. Firstly, a more complete framework is needed for measuring the degree of industrial convergence, and a more comprehensive indicator system needs to be constructed in the future. Secondly, it is possible to conduct a more in-depth study on the impact of the convergence of other industries on CE to provide more effective policy recommendations for reducing it.

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Conflict of Interest

The authors declare no competing interests.

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